2017

Detection of DDoS Attacks against the SDN Controller using Statistical Approaches

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DETECTION OF DDOS ATTACKS AGAINST THE SDN CONTROLLER USING STATISTICAL APPROACHES

A thesis submitted in partial fulfillment of the
requirements for the degree of
Master of Science in Computer Engineering

By

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2017
Wright State University

WRIGHT STATE UNIVERSITY

GRADUATE SCHOOL

December 7, 2017

I HEREBY RECOMMEND THAT THE THESIS PREPARED UNDER MY SUPERVISION BY Basheer Husham Ali Al-Mafrachi ENTITLED Detection of DDoS Attacks against the SDN Controller using Statistical Approaches BE ACCEPTED IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF Master of Science in Computer Engineering.

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ABSTRACT

Al-Mafrachi, Basheer Husham Ali. M.S.C.E., Department of Computer Science and Engineering, Wright State University, 2017. *Detection of DDoS Attacks against the SDN Controller using Statistical Approaches.*

In traditional networks, switches and routers are very expensive, complex, and inflexible because forwarding and handling of packets are in the same device. However, Software Defined Networking (SDN) makes networks design more flexible, cheaper, and programmable because it separates the control plane from the data plane. SDN gives administrators of networks more flexibility to handle the whole network by using one device which is the controller. Unfortunately, SDN faces a lot of security problems that may severely affect the network operations if not properly addressed.

Threat vectors may target main components of SDN such as the control plane, the data plane, and/or the application. Threats may also target the communication among these components. Among the threats that can cause significant damages include attacks on the control plane and communication between the controller and other networks components by exploiting the vulnerabilities in the controller or communication protocols.

Controllers of SDN and their communications may be subjected to different types of attacks. DDoS attacks on the SDN controller can bring the network down. In this thesis, we have studied various form of DDoS attacks against the controller of SDN. We conducted a comparative study of a set of methods for detecting DDoS attacks on the SDN controller and identifying compromised switch interfaces. These methods are sequential

probability ratio test (SPRT), count-based detection (CD), percentage-based detection (PD), and entropy-based detection (ED). We implemented the detection methods and evaluated the performance of the methods using publicly available DARPA datasets. Finally, we found that SPRT is the only one that has the highest accuracy and F score and detect almost all DDoS attacks without producing false positive and false negative.

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ABBREVIATIONS

λ_0	probabilities that low-rate flows pass through normal interface
λ_1	probabilities that low-rate flows pass through compromised interface
α	false positive error
β	false negative error
σ	standard deviation
AMU	attack mitigation units
ARP	address resolution protocol
ASICs	application- specific integrated circuits
ASSPs	application- specific standard products
C_i^+	upper Side cumulative sum
C_i^+	lower side cumulative sum
CD	count-based-detection
CDPI	control-data-plane-interface
CSL	control switch link
CUSUM	cumulative sum
d	function of false positive error and false negative error
D_n^i	detection (log-likelihood ratio)
DARPA	defense advanced research projects agency
DDoS	distributed denial of services attack
ED	entropy-based-detection

F_o^i	flow observation per interface
H	decision interval of CUSUM
H_0	normal interface in SPRT
H_1	compromised infected interface in SPRT
HTTP	hypertext transfer protocol
ICMP	internet control message protocol
IP	internet protocol
K	reference value
LAN	local area network
M_0	target mean
M_1	out of control mean value
MAC	media access controller
MITM	man-in-the-middle
N^+/N^-	counter for (C_i^+) and (C_i^-) respectively to record when these two values start to increase above target mean (M_0).
NBIs	northbound interfaces
ONF	open networking foundation
P	probability of each unique IP destination address is calculated
PD	percentage-based-detection
RTT	round time trip
SD	statistical differentiation
SDN	software defined networking
SLAs	services agreement and contracts

SPRT	sequential probability ratio test
STRIDE	spoofing, tampering, repudiation, information disclosure, denial of service attack, and elevation of privilege
SVM	support vector machine
SW	switch
TCP	transmission control protocol
TLS	transport layer security
UDP	user datagram protocol
W	windows size
TPR	true positive rate
FPR	false positive rate
TNR	true negative rate
FNR	false negative rate
PPV	positive predictive value
NPV	negative predictive value
FOR	false omission rate
FDR	false discovery rate

ACKNOWLEDGMENTS

I would like to take this opportunity to extend my thanks to my advisor, Dr. Bin Wang, for his patient guidance, encouragement and advice, and especially for his confidence in me. He has been supportive of my career goals and who worked actively to provide me with the protected academic time to pursue these goals.

I would also like to thank the committee members Dr. Yong Pei and Dr. Mateen Rizki for their time and advice throughout this project. I really appreciate their input and expertise in evaluating this thesis.

I would like to express my sincere gratitude to Higher Committee for Education Development in Iraq (HCED) to support and fund me during my studying abroad. HCED is an excellent association in Iraq that gives an opportunity to intelligent students to study abroad. This work would not have been possible without the financial support of them.

Finally, I would like to thank my father, my mother, my wife, the rest of my family, and my friends for their encouragement, love, and endless support. They are always supporting and encouraging me with their best wishes.

DEDICATION

To my mother Um-Omar and my wife Um-Ibrahim

CHAPTER 1: INTRODUCTION

This chapter presents an overview of this thesis. We identify the problem to be studied and the significance of this research. This chapter also explains the goals and outline of this thesis.

1.1 Overview

In traditional networks, traffic flows are transferring through networking devices such as routers and switches that are distributed around the world. Networking devices are responsible to control and forward traffics. Although these traditional networks are widespread and popular, they have several drawbacks. First, they do not provide flexibility to researchers to do their experiments and add new features or protocols [1], [2]. Second, traditional networks are not programmable, so they cannot accept new commands to improve their functionality. Third, the cost of networking devices is very high because each device contains both the control and data plane [3].

However, Software Defined Networking (SDN) fixes the problems of traditional network. SDN is a programmable and virtualized network that helps researches to insert their new ideas. SDN separates the control plane from the data plane. The control plane is responsible for handling information whereas the data plane is responsible for forwarding data. By using SDN, researchers can do their own experiment in network without disturbing other people who depend on it. Multiple network devices can be managed and configured by using single device which is the control plane [4]. This may lead to reduce the time of recovery when errors happened. Finally, SDN is cheaper than traditional netwo-

rks [3], [5].

Because the SDN infrastructure is more flexible, programmable, and simpler than the traditional networks, it can be deployed in many different types of networks such as private networks, enterprise networks, and wide area networks [6] . Unfortunattely, SDN has many challenges that need to be addressed. Scalability, performance, and security are some of the challenges that face SDN.

Cyber-attacks have become a dangerous weapon against famous companies, banks, government units, and universities. These attacks may lead to destroy, steal, expose, change, and gain important information. Attackers can exploit vulnerabilities and get unauthorized access to servers or clients and do their malicious purposes. SDN has problems and vulnerabilities that attract attackers to perform their malicious actions.

There are many kinds of threat vectors that have been determined in SDN [8]. Some of these threats target main components of SDN such as the control plane, the data plane, or application. Other threats target communication among these components. The most dangerous threat attacks the control plane component and the communication between this component and others. These threats would be done by exploiting the vulnerabilities or bugs that exist in the controller or communication protocols. Attackers would be able to control the whole network if they can successfully attack the control plane.

Controllers of SDN and their communications are subjected to different types of attacks. Spoofing, tampering, repudiation, information disclosure, distributed denial of service attack (DDoS), and elevation of privilege are all kinds of attacks that target the SDN controller [2]. The most dangerous one is DDoS attacks because research shows that

the controller is a vulnerable target of DDoS attacks such as [36], [1], [9], [6], [10], and [11]. If the controller is brought down, the whole network will be stopped.

1.2 Motivation for Attackers

There are too many reasons that induce intruders to target the controller in the SDN. First of all, the controller benefits in SDN as a processing logical unit. Attackers can manage the whole network if they can take over controller [12]. Moreover, controllers are not secure and robust [3]. Controllers such as Beacon, Floodlight, OpenDayligh, and POX have several bugs that attract attackers. Allocation memory space and unexpected stopping for application of controller are some examples [2], [13]. Finally, aggregation of traffic flows toward the controller is another reason [12]. This increases the congestion between controller and switches. It also increases the problem of the scalability in controller [14]. Therefore, attackers can exploit these vulnerabilities and problems in the controller to do their malicious activities.

1.3 Significance

Because of the advantages of SDN, company such as Yahoo, Google, Microsoft, Version, and Deutsche Telekom established Open Networking Foundation (ONF) to develop Openflow specifications and promote utilization of SDN. Other technology companies are also part of this association such as Cisco, Juniper, Broadcom, Dell, IBM, NEC, Riverbed Technology, HP, Broadcom, Citrix, Ciena, Netgear, Netgear, Force10, and NTT [15].

Main component of SDN which is controller and communications between controller and other components are still vulnerable to DDoS attacks. Much research has been conducted to find solutions for security of SDN [2]. Open Networking Foundation (ONF) also has created several security working group to handle SDN security concern

[3]. However, the work is still in its early stage, and much research highlighted many issues that need to be fixed and addressed [16].

This thesis tries to increase the awareness of dangers of DDoS attacks against the controller. It also helps researchers to make controller of SDN more secure. Finally, it also attempts to detect DDoS attacks in its early stage and protect information of people.

1.4 Thesis Goal, Scope, and Outline

The controller of SDN has serious vulnerbilites that attract attackers to lanuch DDoS attacks. The attacks lead to overload the controller with many packet-in messages coming from switches interfaces. The main goal of this thesis is to studies and compares number of statistical approaches for identification of Distributed of Denial of Service (DDoS) attacks that target controller of SDN and locating compromised switch interfaces.

The scope of this thesis is limited to using the datasets that are available in the Lincoln Laboratory website [17]. These datasets were captured at 1998 and 1999 by the group of Defense Advanced Research Projects Agency (DARPA) to evaluate computer network intrusion detection systems.

This thesis is organized as follow. Chapter two presents the literature review of SDN. Chapter three depicts the algorithms that are used for DDoS detection. Chapter four gives results, discussion, and evaluation. Finally, chapter five presents the conclusion and future work.

CHAPTER 2: LITERATURE REVIEW

This chapter presents differences between the traditional and SDN. It also shows main architecture of the SDN. It explains threats faced the SDN in general and the controller of the SDN in specific. Finally, it presents the DDoS attacks and countermeasures in the last part.

2.1 Traditional Networks:

Network transport protocols and distributed control that carry out inside networking devices are responsible for handling and forwarding data at the same time from one place to another. The information transfer in the form of packets is expressed as series of digits 0 and 1 [2]. Although traditional networks are widely spread around the world, they are very complex to be managed, and the model proposed in [18] proves that. The current network has several disadvantages:

First, the traditional networks do not provide enough flexibility for the designers to add new features such as protocols, applications, and security measures to improve the current networks. Changing the traditional networks model is not possible in practice, and it is very hard to complete if possible [1]. For example, the process of adding the IPv6 protocol instead of the IPv4 protocol to improve the traditional networks took more than ten years, and it is still not completely finished [2].

Second, the traditional networks do not have the programmability capability. They cannot accept new commands to improve their functionality. To make it even more complicated, researches who tried to do experiments are not able to insert their new design

in the network without disrupting other people who depend on it. Thus, new ideas went untried and untested [19].

Third, the prices for networking devices such as routers and switches are very high because each device contains both the control plane and the data plane. The cost for deploying and managing the traditional networks also has increased recently for many reasons. Administrators need to buy or rent real estate to place their devices. They also need to recruit and pay for large number of highly skilled employees to provide services to people around the world, where there is a clear increasing scarcity of human resources [3].

There are many reasons behind these disadvantages. First, the data plane that is responsible for forwarding information and the control plane that is responsible for handling data are built together inside each network device as shown in figure 2.1.a. In other words, admins of networks need to configure and adjust each network device to update the whole network. This prevents innovation and decreases flexibility [20].

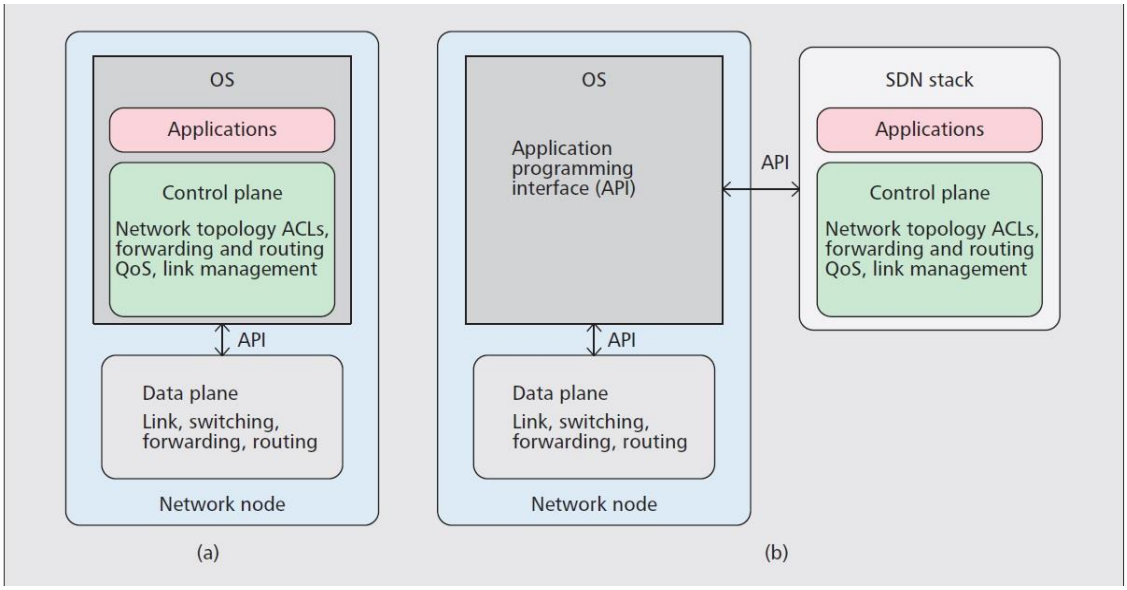


Figure 2.1 Compare between traditional networks and SDN: (a) traditional networks, (b) SDN [5].

Second, many vendors invented different types of networking devices based on their policies and rules. They designed their devices to be a closed software platform. In other words, they prevented access from external interfaces to the control plane, and they made the internal interfaces flexibility hidden and only specified for forwarding process. The barrier of inserting new ideas increased due to this. They did that because they spent a lot of time designing their devices by adding their protocols and algorithms. They are afraid that new research brings down the whole networks if they made open software platform [19].

2.2 Why SDN

Software Defined Networking (SDN) solves the problems that are mentioned above. SDN is a programmable and virtualized network. It separates control plane that takes care of handling information from the data plane that takes care of forwarding data as shown in figure 2.1.b. This produces many positive outcomes:

First of all, administrators can now manage multiple network devices that have different the data plane from a centralized control plane instead of configuring each device individually [4]. The controller can allocate the bandwidth in the data plane [3]. The ability to isolate the data plane from the control plane helps to evaluate, debug, and test new the SDN design before deploying it on real network. This can be achieved by using virtual environment such as Mininet. Mininet is an emulation that can execute multiple number of controllers, switches, and hosts virtually in one single machine [21], [22].

Moreover, researchers can also simply change the current design and insert new protocols based on fixed commands through software program [4]. They can control part of network to run their experiments without disrupting other people who depend on it. They

can isolate their flow from production flow and direct their research flow to find its way through networking devices. This process is done by using open protocol that helps the control plane to control different devices remotely. OpenFlow is one example of protocol that can help the control plane to communicate with the data plane. In this way, administrators can insert their addressing model or security method, and they are also able to replace IP infrastructure easily [19], [20]. This increases the innovation in network design and breaks the fence of inserting new ideas.

Finally, SDN is much cheaper than the traditional networks for many reasons. First of all, single centralized controller can install policies and configuration for multiple networking devices while administrators need to configure each device individually in the conventional networks. This lowers time of deploying and decreases management expenses in SDN. It also fixes problem of increasing scarcity of human resources because one person can manage many data planes through one controller. Moreover, SDN decreases the recovery time from faults and increase error detection and determination. Finally, it also lowers energy consumption such as energy needed for cooling and service function [3], [5].

2.3 SDN Architecture

SDN consists of three main components which are application (application layer), the control plane (control layer), and the data plane (infrastructure layer). Application locates in the upper side, and it contains multiple application logic and Northbound Interfaces (NBIs). The control plane exists in the middle, and it contains NBIs, the control logic, and Control-Data-Plane-Interfaces (CDPIs). Finally, the data plane locates in the

bottom of this design, and it contains multiple CDPIs and forwarding engines as illustrated in figure 2.2.

The NBIs help application plane to communicate with the control plane. Application send down their network requirements to the controller while the control plane send up its desired network behavior, statistics, and events to provide application with abstract view of the whole networks. However, the southbound interfaces or (CDPIs) help network elements that exist in the infrastructure plane to communicate with the control plane. The data plane transfers its statistics, reports, events, and notifications up to the control plane. The control plane sends down its network requirements to the network elements that exist in the data plane, and the data plane obeys rules of control plane [23].

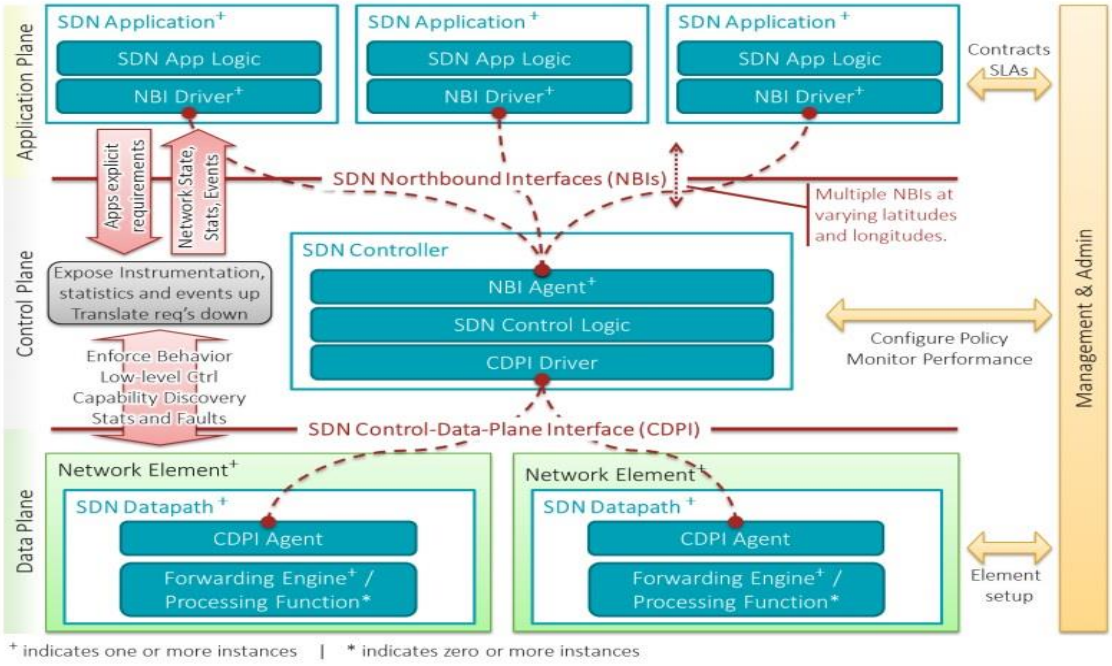


Figure 2.2 SDN components with management [23]

In the right side of the design as shown in figure 2.2, management and admin component is responsible for providing static tasks to all planes that include the control plane, the data plane, and application. The services agreement and contracts (SLAs) will

be configured in the last component which is application plane [23]. Finally, this design also has several agents and coordinators that are spread in the data plane and control plane. These agents and coordinators are responsible to set up the isolation and sharing configuration between the data plane and control plane[7].

2.3.1 OpenFlow Switch

OpenFlow switch is an example about the data plane. This switch offers an open protocol which is OpenFlow protocol that helps researchers to program the flow table that exist in networking devices. Administrators can insert their new protocols and security paradigm. They can also add their addressing method instead of the current IP protocol model. They may simply separate their research flows from the production flows, so they can get comfortably implement and test their new idea without disturbing other people. Flow table, secure channel, and OpenFlow protocol are the three parts of OpenFlow switch as shown in figure 2.3 [19], [24].

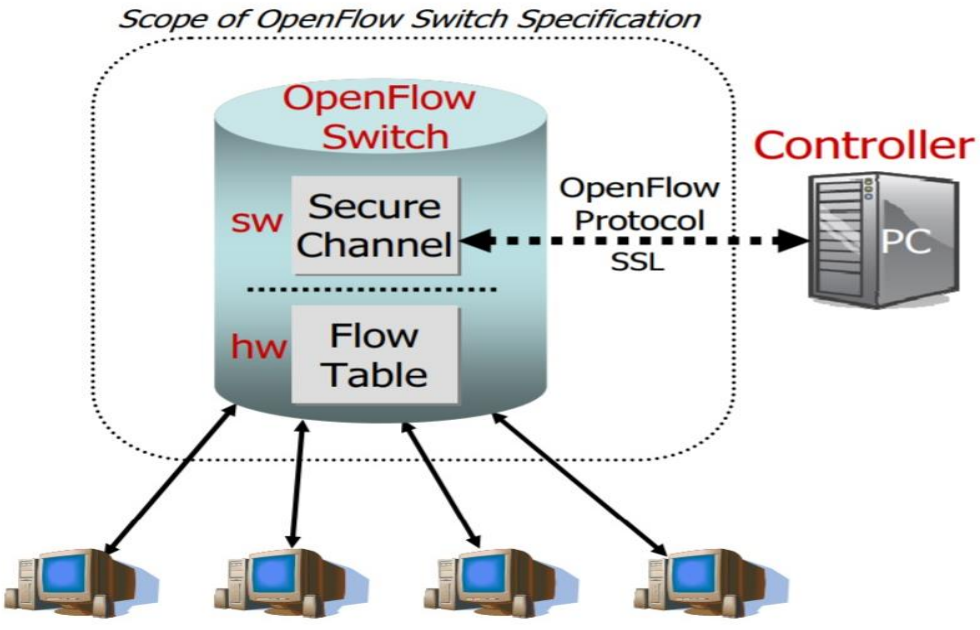


Figure 2.3 OpenFlow switch [19]

This switch consists of three parts. These parts are flow table, secure channel, and openFlow protocol. First of all, OpenFlow switch contains multiple flow tables, and each flow table contains multiple flow entry. Each entry in the table contains three fields. First, packet header is the first field that identifies each flow. The header contains some information such as the ethernet source address, ethernet destination address, type of ethernet, IP source address, IP destination address, TCP port number, and TCP port number. The action is the second field that helps switch in handling the received flow's packets. Statistics is the third field that keeps information about packets such as number of packets, number of bytes, and time since the last packet match flow. In addition, secure channel is the other part of this switch. It helps instructions and packets to be send back and forth between the controller and switch in a secure environment. Moreover, the last part is OpenFlow protocol that offers an open and standard path for controller to communicate with switch [19], [24].

There are three main types of actions that can be taken by this switch. The first action forwards a flow to a given port to let packets reach their destination. This case is applied when there are rules in flow table about how to handle a received flow. The second action encapsulates and forwards only first packet of each flow to the controller through secure channel. This happens when there is no saved action in flow table about how to process that flow. The reason for encapsulating and forwarding only first packet of each flow toward controller is to reduce the controller overhead or bottleneck [2]. In other case, all packets within each flow send to the controller for processing [19]. After processing a flow in the controller, response will be sent and saved in the corresponding flow entry. The third action drops a flow. The reason for this action is to prevent attacks such as the DDoS

attacks, or it could be to decrease fake broadcast traffic from end users [19]. Finally, these actions or rules are installed by the controller in the data plane. These actions could be installed proactively by the controller which means on its accord. In other hands, the controller can choose to install these actions reactively based on notifications or reports from switches if there are no matches between existing rules and incoming packets [25].

2.4 Key Challenges

The main components of SDN design have many challenges that need to be addressed. The scalability, performance, and security are some of these challenges that face the SDN. In this section, causes of each challenge that face one or more of SDN components will be explained. Finally, few proposed solutions for these problems will also be presented in this section.

2.4.1 Scalability

It is hard to define the scalability, and there is no fixed definition for it. Many researches define it as the size of application parallelization for many different devices. However, others define it as the size of network, processor, and/or system to process and handle the increasing amount of load. In general, it is a characteristic that should be positive and desired regarding a network, system, design, and so on [26], [27], [14]. In the SDN, system can be called scalable if controller can stay efficient when administrators increase number of switches.

There are many reasons for controller to be non-scalable. First of all, decoupling the control plane from the data plane is one reason for increasing problem of scalability in the SDN. This separation requires two points. One of them is that management of whole networks may be achieved from remote centralized device which is the controller. The other one is that switches are only responsible for forwarding flows. In this case, switches

send messages to the controller to know rules about handling packets, and the controller responses with instructions. This increases the overload between controller and switches [14].

Furthermore, another reason for scalability problem in SDN increases the number of hosts such as desktops and laptops and networking devices such as routers and switches in the network. When many nodes are added in the network, number of events or flow requests that need to be handled by controller would also increase. This makes the controller as a bottleneck point especially when controller has limited computation resources like memory and processor. For example, NOX controller can process 30K request per second in the small networks [28]. On other hand, NOX cannot perform well in the network that has many nodes such as large data centers [29], [30]. Controller bottleneck also creates delay in the data plane programing because time needed to handle flow is increased in the control plane. As a result, this decreases speed of whole networks [14].

Finally, increasing the distance between the controller location and networking devices is another reason for the scalability problem in SDN. When the distance is increased, the flow setup time such as adding, deleting, or updating in switch flow table may be increased. The flow setup can be measured by calculating the round time trip (RTT) which is the time of processing packets between the switches and the controller. Whenever RTT is high, the flow setup delay is high. This introduces congestion in the data plane and the controller, and it also results in increasing delay in the whole network [14], [31], [3].

2.4.2 Performance

The performance is the processing speed of devices in network such as switches, routers, controllers, and hosts depending on response time (latency) and amount of data that can be processed (throughput) [3]. There are many reasons to decrease the performance in SDN. First of all, number of controllers in the network can lead to performance problem. When there are more than one controller in the network, the response time of controller for flow request may be decreased. This increases performance and vice versa [32]. The location of controller has effect on performance as mentioned in previous section [31].

In addition, type of network processing technology has an impact on the performance of the whole network. Multicore (CPUs/ GPPs) may achieve highest flexibility, but it cannot achieve performance greater than 10 Gigabit per second [33]. NPU/ NFP is better than the multicore process because it provides throughput of approximately over 100 Gigabit per second for each device. This improves the performance, but it decreases the flexibility of networks. PLD/ FPGA can do a flow processing for over 200 Gigabit/s per device. This is used in network processing and telecommunication. It increases the performance and deceases the flexibility. Application- specific standard products (ASSPs) are the base for highest performance network. It is used to implement Ethernet switching because it supports over 500 Gigabit/s switching. The main disadvantage of this technology is that it lowers flexibility. Application- specific integrated circuits (ASICs) are another type of flow processing unit. This processor built in Cisco, Juniper, and Huawei system vendors. ASICs offers highest cost, benefit, and performance, but it does not provide higher flexibility as shown in figure 2.4.

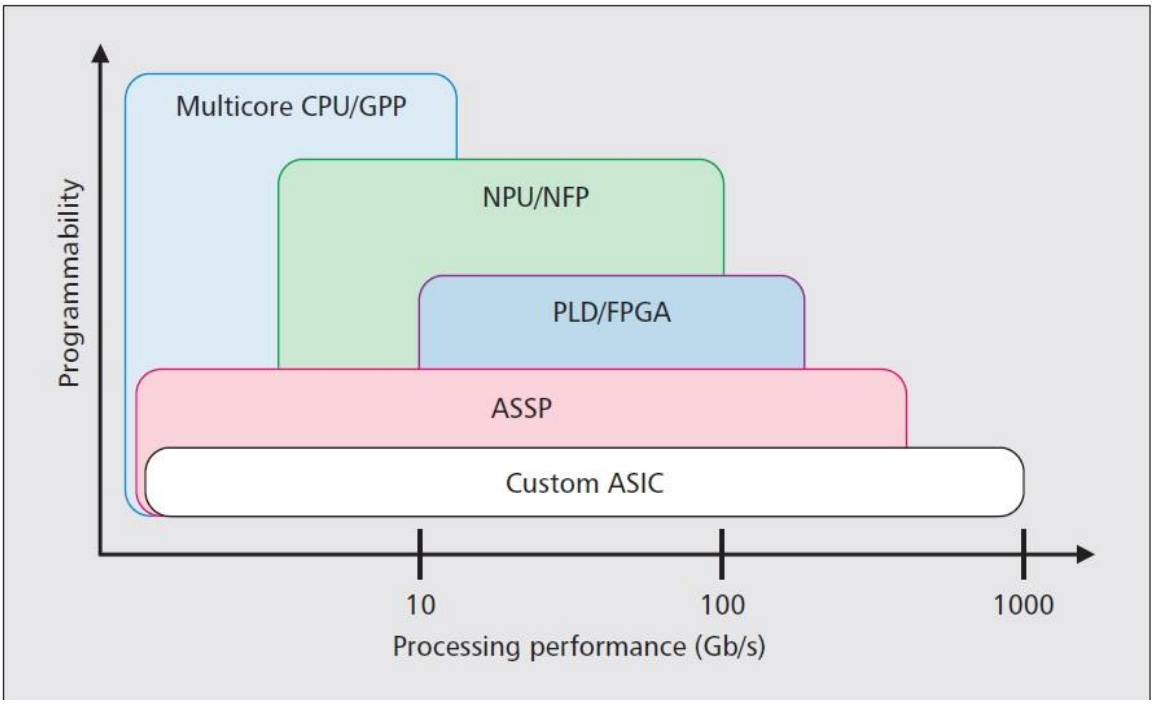


Figure 2.4 Network processing [3]

Therefore, hybrid approach is the perfect solution for the previous problems in order to offer high flexibility and performance at the same time. For example, building design that contains PLD, NPU/NFP, and CPU/GPP can produce hybrid programmable platform [3]. Lookup performance has an impact on the performance. Packet switching throughput can be improved up to 25% if commodity network interface cards are used in Linux [34]. Improving hardware acceleration can lead to increase performance by 20% [35]. Current implementation of OpenFlow switch leads to unacceptable performance, and modification on OpenFlow protocol can increase the performance and reduce the overhead [36], [37].

2.4.3 Security

Cyber-attacks have become a dangerous weapon against famous companies, banks, government units, and universities. Malicious attack destroy, steal, expose, change, and gain important information. Unfortunately, the SDN has problems and vulnerabilities that

attract attackers to perform their malicious actions. In general, there are many threat vectors that are determined in SDN. These threat vectors in SDN and problems in the OpenFlow model will be presented in the next two sections.

2.4.3.1 Threat Vectors in SDN

According to [8], there are seven types of threats vectors that are identified in the SDN as shown in the figure 2.5. Some of these threats are specific to the SDN while others are popular in the traditional networks as shown in table 1. The first threat vector fakes or forges traffic flows that transfer between switches. Defective machine or malicious devices may be the main cause for that threat. Attackers can use this vector to launch Denial of Services attacks (DoS) against networking devices such as switches. The second threat vector attacks switch devices. The main cause of this attack is vulnerability in switches devices. By exploiting this threat, attackers can send traffic flows to other switches to wreak havoc in the network. They can also slow down packets movement in the network.

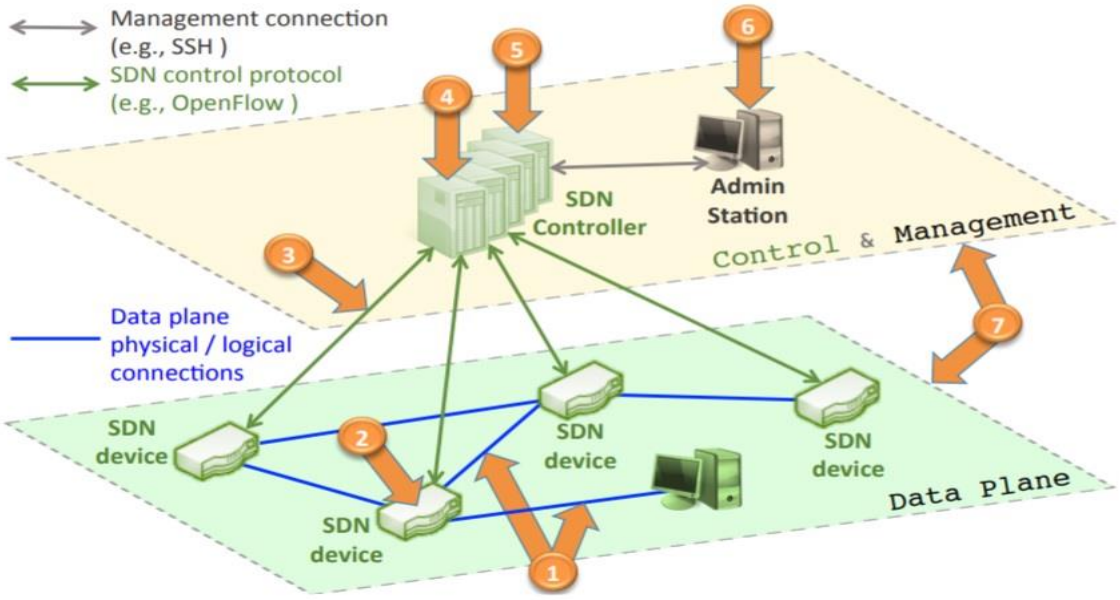


Figure 2.5 Main threat vectors of SDN architectures [8]

The third threat vector attacks on the control plane communications. By exploiting this threat, attackers can forge traffic flows and send many requests to the controller to overload it. This generates the DDoS attacks toward controller. The main reason for this attack is the weakness in TLS/SSL protocol [38]. The fourth vector attacks against the control plane by exploiting the vulnerabilities in the controller. Attackers may bring down the whole network if they can successful attack the control plane. The fifth threat is lack in ability to establish a communication between management plane and controller. The third, fourth, and fifth threat vectors are the most dangerous attacks because attackers can lunch the DDoS attacks and bring down the whole system. These vectors are more specify to the SDN as shown in table 1 [2], [8].

Threats	Specific to SDN?	Consequences in SDN
Vector 1	no	may lead to DoS attacks
Vector 2	no	the impact is potentially increased
Vector 3	yes	communication with controller may be explored
Vector 4	yes	attacking controller can shutdown whole network
Vector 5	yes	deploying malicious application in controller
Vector 6	no	the impact is potentially augmented
Vector 7	no	difficulties of fast recovery when faults happen

Table 1 SDN Specific Versus Nonspecific Threats [2], [8]

The sixth threat vector attacks on administrative stations. Finally, the seventh threat vector is due to lack of trusted resources of remediation and forensics. These help to identify attacks and lead to fast, secure, and correct recovery [8].

2.4.3.2 STRIDE Model Applied to SDN

According to [2], STRIDE is based on spoofing, tampering, repudiation, information disclosure, denial of service attacks, and elevation of privilege. The OpenFlow networks are subjected to these types of attacks. Table 2 summarized these attacks based

on security properties and examples. First of all, spoofing is a malicious practice in which attackers can hide their identity and send fake packets or traffic flows based on victim identity to receiver. The main reason for this attack is lack of appropriate verification and authentication [39]. Address Resolution Protocol (ARP) spoofing, ARP routing poisoning, or ARP cashing poisoning is an example of spoofing technique. In the traditional networks, attackers send their MAC address along with the IP address of victim to the switch in the local network area (LAN). As a result, any traffic that have IP address of victim will be directed to the machine of attackers. In this way, attackers may change traffic, intercept data frame in the network, and stop flows traffic if they want. This process happens due to lack of authentication to determine the verification of sender. This triggers many other attacks such as man-in-the-middle (MITM), DoS, and session hijacking attacks [40]. In SDN, the controller plays a role of forwarding packets functionality assuming that it has information of MAC-IP mapping. The controller receives pairs of MAC address and IP address of victim and forward them to targeted hosts or switches to store them in cash table [41]. Finally, attackers can spoof controller address. This helps attackers to control the whole network and install rules in the forwarding devices [2].

Attack	Security Property	Examples
Spoofing	Authentication	Forged ARP, IP and Mac address spoofing, and IPv6 router advertisement.
Tampering	Integrity	Rule installation, counter falsification, and modification affecting networking devices.
Repudiation	Non-repudiation	Modification for source address forgery and rule installation.
Information disclosure	Confidentiality	Side channel attacks to explore flow rule setup.
DoS	Availability	Flow requests to overload control plane.
Elevation of privilege	Authorization	Control plane take over exploiting implementation flaws.

Table 2: STRIDE attacks in OpenFlow networks [2]

In addition, tempering is another form of attack that target the OpenFlow network. Attackers can intercept stored or transported data, and they can modify, change, remove that information to serve their need. This attack compromises integrity because intruders can do their actions without receiving alarms in all receivers. In SDN, intruders can intercept and change OpenFlow controller communication, and they can overwrite the controller rules [39]. Counter falsification is an example of this type of attack. Intruders try to guess existed flow policy and then tamper packets to increase counter. This malicious action increases billing for customer and takes nonoptimal decision by load balancing algorithm [2].

Furthermore, repudiation is another type of attack in the SDN. Separating the control plane from the data plane increases the probability to trace malicious nodes and hidden communications [42]. However, attackers try to do malicious manipulation or tempering that lead to change identification or authoring data in order to access the user to wrong data. This is happened due to lack of monitoring capabilities and tracing of the controller or networking devices in the SDN [39], [43].

Moreover, the OpenFlow network also faces an attack that is called information disclosure. The goal of this attack is to collect information about system that is publicly available such as path levels, response time, and version number. The main problem for this attack is due to the lack of confidentiality that is responsible for preventing access to certain information that open the door to expose sensitive information [39]. For example, attackers can get information about network operation when rule flows setup is in place. The controllers in the SDN install flow rules in switch in two different ways which are either reactive or proactive. when the flow rules installation is reactive, this means that

installation is based on notifications or reports from switches. Attackers can measure the delay between first flow and the next one. This creates an attack called fingerprinting which is the first step to create DoS attack [44]. However, when the flow rules installation is proactive, attackers cannot easily guess the forwarding flow rules, but it is still possible [25].

Finally, the SDN presents problem of elevation of privilege attacks. Attackers can have legitimate privilege of administrators. By using this attack, attackers can do what administrators do such as opening and changing files and/or even changing user account. Finally, there are no perfect deployment or application to decide whether a certain design is strong or not. For example, while large scale data centers have been installed by Google [45], they ignored the issue of conflicting application using internal conflict resolution and single application blocks [46], [39].

2.5 DDoS Attacks and Countermeasures

The SDN also faces the DoS and/or DDoS attacks. The DoS attacks happen when compromised host targets single system by sending flood of unnecessary traffics. The main goal of this attack is to decrease system availability and prevent legitimate users from accessing available services. If attackers use many hosts instead of only one to target single system which is the controller, this is called DDoS attacks. DDoS has harmful consequences on the controller of the SDN. For example, businessmen who are offering online services can loss large amount of money if attackers can carry out DDoS successfully against these services [47].

In the normal case of the SDN, when users tried to communicate with each other within network, they first send packets to their switch that is connected to them. These

incoming new packets will search to find a match with information that are stored in switch forwarding table. The reason for that is that each packet can know its destination. If there are any match, packets follow rules that are associated with the match. For example, dropping packets is one option if there is a match. Another option is forwarding packet to its destination node. However, if there are no matching between packets and information in switch forwarding table, then switch will forward these packets to controller in a form of packet-in messages for processing and getting new flow rule. The communication between switches and controller may be done by using OpenFlow protocol [24]. Controller would decide whether to drop or forward packet to its destination. It is responsible for handling new packets and sending new rules to switches [19].

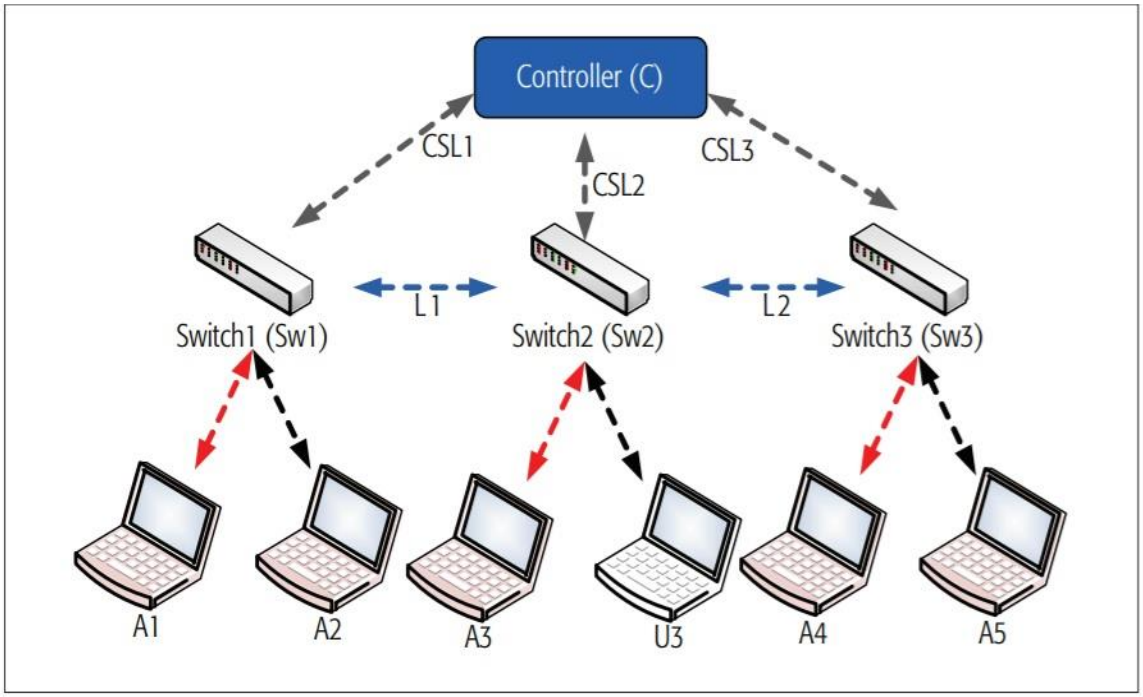


Figure 2.6 DDoS attacks in SDN [12]

Considering the previous normal case in the SDN, attackers can lunch DDoS attacks against the controller by following one of next two scenarios. First, attacker hosts (let say A1 and A2) who are under one switch (let say sw1 that is explained in figure 2.6)

may send large number of new low-rate packets to their switch. IP addresses for these new packets may also be spoofed and may not existed in switch flow table rules. As a result, switch may generate many packet-in toward controller to get response. This makes the link between compromised switch and the controller (CSL1 in figure 2.6) under congestion and overload the controller with many new packet-in requests.

The second scenario is that attackers under multiple switches for same controller (let say A1 to A5) send many new spoofed IP packets to their switches. This makes links between these switches and controller (CSL1, CSL2, and CSL3) are all congested. This creates an attack that is called blind DDoS attacks as stated in [48] . It is very hard to detect because attack load is divided among switches. Finally, both cases result in denying legitimate requests and decrease system availability [12].

Finally, DDoS attacks against the controller have several characteristics that make identification process very hard to be done by conventional detection methods. First of all, there is not many benefits of performing detection process in the switches because switches may not be able to detect this attack completely. The reason for that is attackers may be distributed and located under different switches, so switches receive low traffics which seem to be normal. In addition, the controllers are not able to decide whether they are affected by the DDoS attacks or not according to number of receiving traffics only because attacks could be achieved by benign traffics. Furthermore, traditional detection methods of DDoS attacks such as ICMP flooding, TCP SYN flooding, and HTTP flooding require to have specific characteristics. However, traffics features that are generated toward the controller in the SDN network are different from these knowing flooding. This makes it impossible for traditional techniques to detect the DDoS attacks against the controller in

the SDN [6]. Therefore, this thesis focuses on finding a good detection method of DDoS attacks.

DDoS is a difficult problem that needs a real solution due to the reasons that are mentioned earlier. According to [12], the DDoS solutions can be classified to whether they are intrinsic solutions which are focused on the SDN components and their functionality elements or extrinsic solutions which are focused on network flows and their features. These two main classifications can be also categorized to further classification. Intrinsic solutions can be classified into scheduling-based and architectural-based. However, extrinsic solutions can be categorized into statistical and machine learning based.

2.5.1 Intrinsic Solutions

According to [12], intrinsic solutions are these solutions that are focused on the SDN components and their functionality elements. They can be divided to either scheduling-based solutions or architectural-based solutions.

Scheduling-based solutions are one of the implementation to protect the controller of the SDN. In [49], H, Shih-Wen et al proposed a solution based on using hash-based mechanism that operates in the control plane to increase the scalability. Switches may generate many packet-in messages toward the controller due to receiving malicious traffics or legitimate traffics from hosts. This increases the congestion and makes the controller as a bottleneck point. Scheduling-based solutions aim mainly to decrease the controller overhead and increase the scalability and reliability. They also help to reduce the transmission delay and failure in response in case of the congestion. These solutions are based on using round-robin model that assigns incoming packets from switches to multiple queues in the controller. The main disadvantage of these solutions is that they cannot

recognize the flash crowd, which is based on sending large number of legitimate flows, from the DDoS attacks. This means they does not have a detection model for the DDoS attacks [12].

Another solution based on scheduling was proposed in [50]. This solution was based on providing different queues for each switch in controller to receive incoming packets. This distributes the allocation of controller processing capacity among switches. This helps to separate packets that are coming from infected switch and these from uninfected switch. This makes the controller to work even if it is under DDoS attacks. This was the main goal of this method because controller failures may stop the whole networks. Although this method separates malicious flows from normal flows, it was not able to distinguish DDoS attacks from flash crowd [12].

Architectural-based solutions are another way to protect the controller in the SDN from DDoS attacks. First of all, C. Dharmendra et al in [51] proposed a solution to fix security and load balancing in SDN. They proposed a model for decoupling application monitoring and packet monitoring from each other. This method has two parts which are main and secondary controller as shown in figure 2.7.

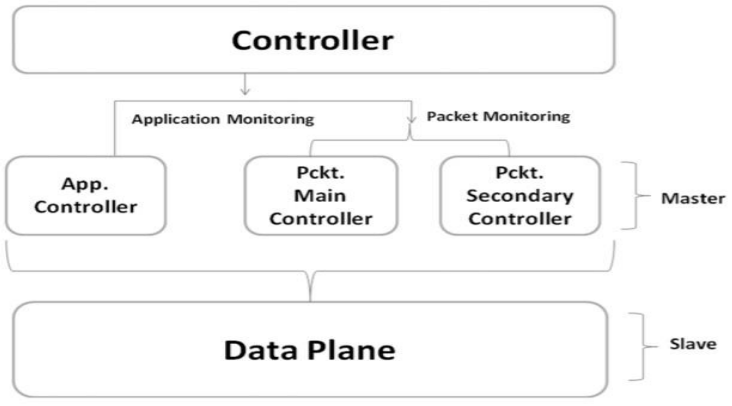


Figure 2.7 Proposed Controller Architecture in [51]

The advantage of this division is that secondary controller can take control if there are failures in the main controller. On other hands, authors did not explain the detection phase. Their design did not differentiate malicious from legitimate flows and consider DDoS attacks and flash crowd identically [12].

Wang proposed FloodGuard which is a defensive method against DDoS attacks. FloodGuard has two modules to do its job. The first one called proactive flow rules analyzer which is in the control plane. In this stage, flow rules were derived in runtime based on dynamic application tracking and symbolic execution. The main reason for this module was to keep SDN running under DDoS attacks. The second module named packet migration which is responsible to cash flows in switches then sending them to the controller by using round- robin scheduling and rate limit. The main reason for this module was to prevent congestion and process flows during flood without dropping out legitimate flows [52].

Finally, control messages and monitoring traffics that are going back and forth between controller and switches may increase congestion. As a result, Z. Adel et al in [53] proposed a solution which is an orchestrator-based architecture for enhancing network-security. This model separated controlling functionality from monitoring and put each one in a module, and both of modules were controlled by an orchestrator. Some kinds of attacks could be determined by getting access to some packets such as DDoS attacks, and this was called low resolution attacks. However, other attacks could be resolved by getting access to all packets in network such as ARP attack, and this was called high resolution attack. Orchestrator entity decide which module should be enabled according to attack type to do

detection with the help of orchestrator instructions. On other hands, this method did not totally mitigate the attack, and packets attack can still be used in the system [12].

2.5.2 Extrinsic Solutions

Extrinsic solutions are these solutions that are focused on network flows and their features. They can be divided to either statistical or machine learning based solutions [12].

2.5.2.1 Statistical Based Solutions

First of all, statistical-based solutions are another approach to protect the controller of the SDN. In [10], D. Kotani proposed a method which is packet-in filtering mechanism to detect the DDoS attacks against the controller. This method was based on recoding the values of packet header by switches before sending packet-in values to the controller. Switches then filter out packets that are less important than others or have the same values of recorded one. However, this method was inactive if the values of new packets header that were generated by attackers are different from the recorded one [6].

In [54], P. Andres et al proposed a method that was called FlowFence to protect control plane based on statistical solutions. In their approach, switches monitor their interfaces to determine whether there is congestion or not by measuring which interface consuming large bandwidth. Then, switches notify the controller if they identify a congestion for a specific link. Because the controller is responsible for assigning bandwidth for links between controller and its switches, the controller limits flow transmission rate for the congested interface to prevent starvation. They believed that their method is simple, efficient, fast, and prevented congestion. However, their method cannot prevent attacks completely, and it only limited the flow transmission rate [12].

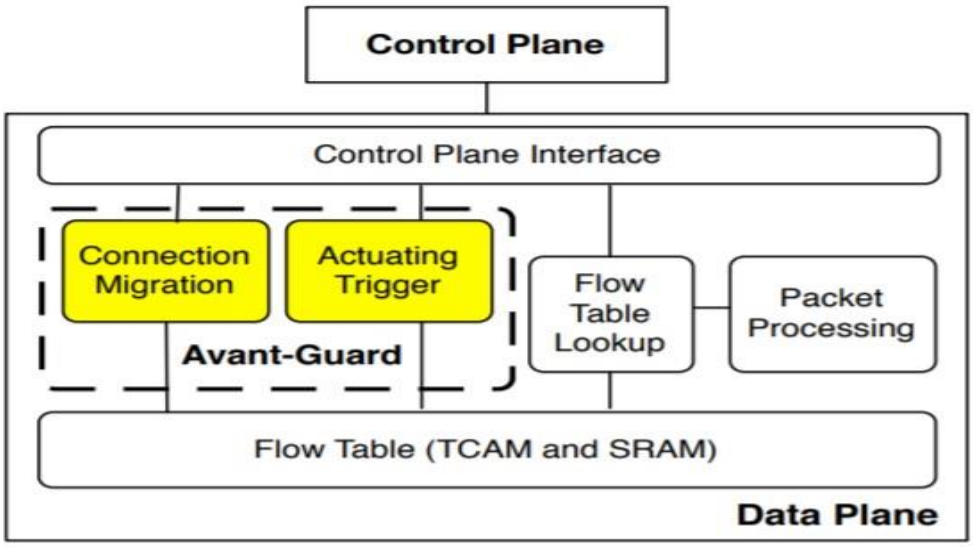


Figure 2.8 Avant- Guard Architecture [55]

In [55], Avant-Guard was proposed to detect the SYN flood which is one kind of DDoS attacks against the controller in the SDN. This framework includes two modules which are connection migration and actuating triggers as shown in figure 2.8. The first module was responsible for classifying TCP/SYN packets requests. If requests were identified as normal, they were directed to its destination. However, if they were identified as malicious, actuating triggers module enables an event for the controller to install flow rule in switch to decrease response time. The drawback of this approach was that it can identify only one type of DDoS attacks which is SYN flood [12].

In addition, detection attack based on entropy variation is another way of statistical approach to protect the controller against the DDoS attacks. There are few works which use entropy-based solution. One of these was suggested by Rui et al in [56]. Their idea was based on calculated entropy for destination IP address. If value of entropy is larger than certain threshold, then there are no DDoS attacks. However, if value of entropy is lower than the proposed threshold, then there are DDoS attacks. The drawback of this method is

that it could not separate malicious from legitimate packets [12]. However, this method helped to achieve disturbed anomaly detection in the SDN and decrease congestion against the controller [56].

Moreover, Chen in [9] proposed another way which is SDNShield to protect the SDN against DDoS attacks. This defense framework was specified for protecting the SDN network edges and the controller. First of all, SDNShield builds attack mitigation units (AMU) which are array of software switches at the SDN network edges. These units help to prevent the congestion or bottleneck at the SDN network edges. In addition, AMU helps to protect the controller by installing two filtering platforms. The first one is statistical differentiation (SD) which is responsible for separating the benign flows from malicious flows. The second filter is TCP connection verification which is responsible in doing in-depth investigation for false positive of the first step. This helps to make sure that benign flows were accepted.

Furthermore, another solution for DDoS attacks which was based on anomaly prevention techniques named a multi-criteria-based DDoS-attack prevention was introduced in [57]. In this method, switches send statistical parameters to the controller such as quantity of packets for each flow, numbers of flows entries, and arrival time. The controller in turn receives these parameters and detects the DDoS attacks by using fuzzy inference system and hard decision thresholds. This method could not only detect attacks flows but also drop them based on demands from the control plane.

Finally, a new idea was suggested in [58] which was combining of OpenFlow and sFlow module to detect and mitigate a DDoS attacks on the SDN. Authors of this paper exploited the OpenFlow and sFlow protocol features to detect malicious flows in real time.

Their framework composed three components which were collector, anomaly detection, and anomaly mitigation as shown in figure 2.9. First, they discovered that OpenFlow approach increased communication between switches and the controller. This decreased

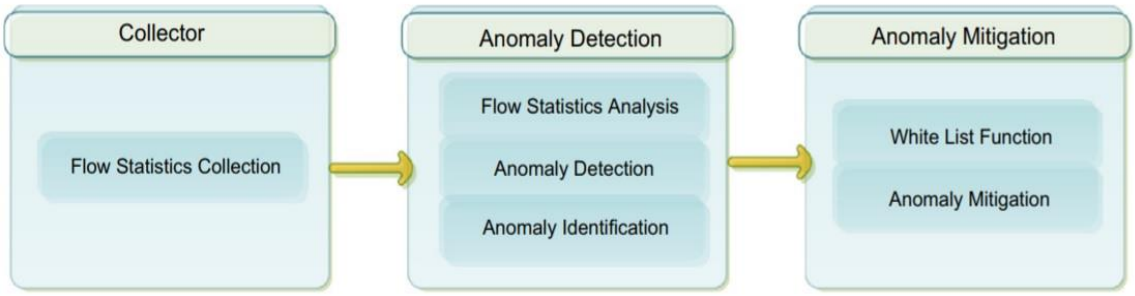


Figure 2.9 Architecture of DDoS Detection and Mitigation that Proposed in [58]

scalability and increased probability of the DDoS attacks against the control plane. Thus, they used sFlow approach instead of OpenFlow approach to separate controller from data collection process and decrease the data collected. Second, they used entropy-based detection for separating malicious and normal flows in both OpenFlow approach and sFlow approach. Third, using anomaly mitigation to block undesired attacks. This module had several advantages. For example, the scalability was improved because they did not need to collect large numbers of flows as in OpenFlow approach. Performance was increased because CPU and memory flow cache usage were minimized. Finally, there were an effective reduction in the communication between the controller and switches that decreases the possibility of overloading the controller.

2.5.2.2 Machine Learning Based Solutions

Machine-learning-based-solutions are another approach to identify DDoS attacks against the controller in the SDN. In these kinds of solutions, the defense mechanism that was trained by feeding free attack flows (training) into machine learning algorithm can

detect attack flows (testing) [12]. Kokila et al. suggested a method to detect DDoS attacks against the controller by using support vector machine (SVM) classifier [59].

SVM is one type of large margin classifier and kind of machine learning. It is used primarily to find the decision boundary or a model that separates points to two or more groups. For example, let us assume that we have a dataset of training samples, and each point of these samples is marked as belong to one or another group. SVM creates a model to separate these current data by drawing a clear decision boundary or gap that is as wide as possible. The data points that created this boundary are called the support vector points. Then, this model categorizes new datasets on the same space according to which side of the gap they fall [60].

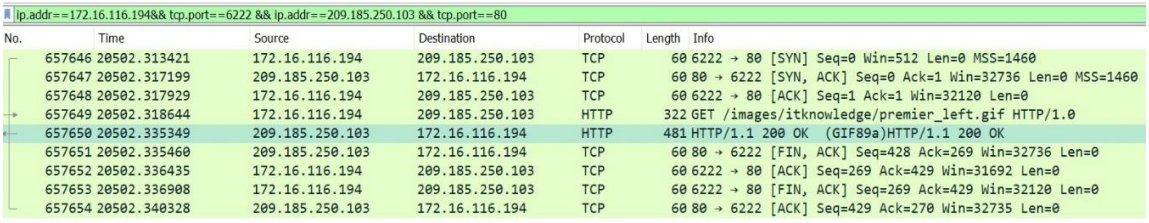
There are several intuitions behind the SVM. First, the large margin classifier may help decrease the errors in calculation. This improves the classification task because points that are located near the decision boundary have uncertain classification decision. In other words, the uncertainty in the classification decision may be decreased by making the margin large enough. Second, as long as the margin is large enough, the model may have little choices of where data fit. As a result, the memory capacity may be decreased, and this increases the ability to correctly classify data [60]. For these reasons, authors in [59] used SVM as a classifier to detect DDoS attacks. They found that their algorithm is better than other machine learning algorithms. However, their algorithm could only detect attacks without trying to mitigate these attacks [12].

CHAPTER 3: METHODOLOGIES

This chapter explains flow classifications in the first part. In the second part, it depicts algorithms that are used to identify the compromised switch interfaces and detect DDoS attacks against the controller in the SDN. Sequential probability ratio test (SPRT), count-based detection (CD), percentage-based detection (PD), entropy-based detection (ED), and cumulative sum (CUSUM) are these algorithms.

3.1 Flow Classification

Flows are sequence of packets that share same characteristics. These characteristics could be (source IP address, destination IP address, source port number, destination port number, and/or protocol type). All of these information can be extracted from header of each packet. Flows of TCP and UDP based protocols might be these five tuples. However, flows of ICMP protocol could be grouping all packets that have same source IP address, destination IP address, and protocol type because ICMP packets do not have port numbers in their header.


ip.addr==172.16.116.194&& tcp.port==6222 && ip.addr==209.185.250.103 && tcp.port==80

No.	Time	Source	Destination	Protocol	Length	Info
657646	20502.313421	172.16.116.194	209.185.250.103	TCP	60	6222 → 80 [SYN] Seq=0 Win=512 Len=0 MSS=1460
657647	20502.317199	209.185.250.103	172.16.116.194	TCP	60	80 → 6222 [SYN, ACK] Seq=0 Ack=1 Win=32736 Len=0 MSS=1460
657648	20502.317929	172.16.116.194	209.185.250.103	TCP	60	6222 → 80 [ACK] Seq=1 Ack=1 Win=32120 Len=0
657649	20502.318644	172.16.116.194	209.185.250.103	HTTP	322	GET /images/itknowledge/premier_left.gif HTTP/1.0
657650	20502.335349	209.185.250.103	172.16.116.194	HTTP	481	HTTP/1.1 200 OK (GIF89a)HTTP/1.1 200 OK
657651	20502.335460	209.185.250.103	172.16.116.194	TCP	60	80 → 6222 [FIN, ACK] Seq=428 Ack=269 Win=32736 Len=0
657652	20502.336435	172.16.116.194	209.185.250.103	TCP	60	6222 → 80 [ACK] Seq=269 Ack=429 Win=31692 Len=0
657653	20502.336908	172.16.116.194	209.185.250.103	TCP	60	6222 → 80 [FIN, ACK] Seq=269 Ack=429 Win=32120 Len=0
657654	20502.340328	209.185.250.103	172.16.116.194	TCP	60	80 → 6222 [ACK] Seq=429 Ack=270 Win=32735 Len=0

Figure 3.1 Flow Sample from Wireshark about Flow [17]

For example, (172.16.116.194: 6222 -> 209.185.250.103: 80 TCP) is a TCP flow sample from dataset that is called “outside tcpdump data” that was captured on the 5th day of April in 1999 [17]. This flow has (9) packets which is simply explained steps of connect-

ion between two nodes. All of these packets share common information such as protocol name, IP source address, IP destination address, destination port number, and source port number. The first three packets are [SYN], [SYN/ACK], and [ACK] which are the three-way handshaking in TCP to start connection. The fourth and fifth packets are exchanging information. The last four packets are responsible to close the connection.

In SDN architecture, each switch has flow table that contains multiple flows entry. Each entry has rule so that switch can know how to handle each incoming packet. When users tried to communicate with others, they send packets to its switch. These incoming packets are grouped to form flows. The incoming flows look at flow table in switch to find a match. If there are a match between incoming flow and flow entry, incoming flow will follow rule associated with flow entry. However, if there are no match, then a switch may generate packet-in message toward the controller to get new flow rule. Finally, the controller installs new flow rule in flow table so that switch can handle a flow [24], [19].

However, attackers could be located in any computer device as shown in figure 2.6. They tend to send to their switch large number of new low-traffic flows that are not presented in that switch flow table. The new flows will induce switch to generate many packet-in messages toward the controller. This overloads the controller with large number of requests and leads to the DDoS attacks. Attackers also tend to send low-traffic flows because these flows will save attackers' time to congest the controller [6].

The main aim of classification is to identify DDoS attacks by classifying these flows to either low-traffic flows (malicious flows) or normal flows. Let consider (F_o^i), where (o) is a sequence observations of different flows (F) that injected an interface (i) of the SDN switch. (F_o^i) is low flow if total number of packets within this flow is lower than

or equal to certain threshold. However, (F_o^i) is normal flow if total number of packets within this flow is larger than that threshold. The (F_o^i) can be defined as follow [6]:

$$(F_o^i)=\begin{cases}1, & \text{if number of packets} \leq \text{Threshold} \\ 0, & \text{if number of packets} > \text{Threshold}\end{cases} \quad (3.1)$$

3.2 Detection Algorithms

The main goal for this stage is to identify the affected interface. Five different type of algorithms that were used to decide whether switch interface (i) is compromised or not.

3.2.1 Sequential Probability Ratio Test (SPRT)

SPRT is the first algorithm that was developed by Wald, and it is a specific sequential hypothesis test based on mathematical calculation [61]. It uses two hypothesizes which are H_0 and H_1. H_0 means that interface is normal whereas H_1 means that interface of switch is compromised. The compromised interface (H_1) is injected by large number of low-traffic flows whereas normal interface is injected by large number of normal flows.

In reality, detection process produces two types of error which are false positive and false negative. False positive error is benign interfaces (H_0) that are falsely identified as compromised interfaces (H_1). False negative error is the compromised interfaces (H_1) that are falsely identified as benign interfaces (H_0). To avoid these two types of errors, value of false positive error should not exceed a specified value of (α), and value of false negative error should not exceed a specified value of (β).

In [6], SPRT was used to decide whether the interface (i) is compromised or not by considering a sequence of (n) which is observation of normal and compromise flows (F_o^i) where (o) is the series of observation (o=1,2,3,…,n). These sequences of flows observation are obtained from the first stage which is flow classification. According to SPRT method,

(D_n^i) is a detection function that can be defined as a log-likelihood ratio of (n) flows observation, whether they are normal flow or low-traffic flow, for certain interface (i). Therefore, the equation for (D_n^i) is the following [6]:

$$D_n^i = \ln \frac{pr\left(F_1^i, \ldots., F_n^i \middle| H_1\right)}{pr\left(F_1^i, \ldots., F_n^i \middle| H_0\right)} \tag{3.2}$$

Assuming (F_o^i) is identically distributed and independent [6], Thus, D_n^i will be:

$$D_n^i = \sum_{o=1}^{n} \ln \frac{pr\left(F_o^i \middle| H_1\right)}{pr\left(F_o^i \middle| H_0\right)} \tag{3.3}$$

Because F_o^i is a Bernoulli random variable [6],

$$pr\left(F_o^i=1 \middle| H_0\right) = 1 - pr\left(F_o^i=0 \middle| H_0\right)=\lambda_0 \tag{3.4}$$

$$pr\left(F_o^i=1 \middle| H_1\right) = 1 - pr\left(F_o^i=0 \middle| H_1\right)=\lambda_1 \tag{3.5}$$

Where λ_0 is less than $\lambda_1$because normal interface is less likely to be injected with low-traffic flows.

This detection can be a one-dimensional random walk. This means if C_o^i which is total number of packets of F_o^i are less than or equal to certain threshold (which is 3) then (F_o^i)=1 and the walk moves upward one step. However, if C_o^i are larger than the threshold then (F_o^i)=0 and the walk moves downward one step [6]. Therefore, the new equation for D_n^i will be:

$$D_n^i = \begin{cases} D_{n-1}^i + \ln \dfrac{pr\left(F_o^i=1 \middle| H_1\right)}{pr\left(F_o^i=1 \middle| H_0\right)}, & C_o^i \leq \text{threshold} \\ D_{n-1}^i + \ln \dfrac{pr\left(F_o^i=0 \middle| H_1\right)}{pr\left(F_o^i=0 \middle| H_0\right)}, & C_o^i > \text{threshold} \end{cases}$$

$$= \begin{cases} D^{i}_{n-1} + \ln \frac{\lambda_1}{\lambda_0}, & C^{i}_{o} \leq \text{threshold} \\ D^{i}_{n-1} + \ln \frac{1-\lambda_1}{1-\lambda_0}, & C^{i}_{o} > \text{threshold} \end{cases} \quad (3.6)$$

Where $D^{i}_{0}=1$.

Now, the value of D^{i}_{n} compares each time with the upper threshold (A) and lower threshold (B). If value of D^{i}_{n} is smaller or equal to (B), then the interface (i) is H_0 and terminate the test. If value of D^{i}_{n} is larger or equal to (A), then the interface (i) is H_1 and terminate test. Otherwise, monitor will continue with additional observation. The value of (A) and (B) can be calculated as shown in equation (3.7) [6], [61]:

$$\begin{cases} A = \ln \frac{\beta}{(1-\alpha)} \\ B = \ln \frac{(1-\beta)}{\alpha} \end{cases} \quad (3.7)$$

3.2.2 Count-Based Detection (CD)

CD is another approach that is used to identify DDoS attacks and locate the compromised interface. This method is based on the number of low-traffic flows. The result of first step that is explained in (3.1) which is classifying flows to either low-traffic flows or normal flows are used as an input to this method. In this method, normal flows are ignored, and low-traffic flows are gathered into small groups or window size based on either timeslot or number of packets. Number of low-traffic flows are calculated per group, and the result is compared with certain threshold. If comparison result is larger or equal to threshold, then attack is detected. However, there is no attack if result of comparison is lower than threshold. Finally, comparison process will go through all groups to decide whether certain interface is infected or not [6].

3.2.3 Percentage-Based Detection (PD)

PD is another method that is also used to detect DDoS attacks against the controller. It also uses to determine whether interface is compromise or not. This method is based on finding percentage of low-traffic flows. This method has two main components which are windows size and threshold. First, the results of low-traffic flows classification from the first stage are grouped to small groups size based on either number of packets or timeslots. Second, percentages of low-traffic flows are calculated by dividing number of low-traffic flows values over number of all flows (normal and low-traffic flows) per group. Third, the results from each group is compared with certain threshold. If percentage of low-traffic flows for one group is larger or equal to a suggested threshold, there is attack for this group. However, if the result of comparison is lower than the threshold, then there is no attack. The process will go through all small groups to find whether the interface is compromise or not [6].

3.2.4 Entropy-Based Detection (ED)

Seyed and Marc proposed a detection method in [11] that is based on calculating incoming packets' entropy that is used to measure the randomness of these packets. When incoming packets are random, the entropy may be high. However, when the randomness is low, the entropy may be also low. This method has two main parts which are windows size and threshold. Incoming packets need to be divided into small groups (windows) based on either timeslot or number of incoming packets. Entropy is calculated for all elements in each window. The value of entropy of each window compares with certain threshold to measure randomness.

In this method, packets are classified to different flows according to certain common of specification such as IP source address, IP destination address, port source

number, port destination number, and protocol type as mentioned earlier in flow classification section. Then, destination IP address for the first packet of each unique flow should be monitored. These monitored IP destination addresses are grouped in windows (W). For each window, hash table of two column is created. The first column contains all unique IP destination addresses, and second column contains number of times that each unique IP appeared as shown in following equation:

$$W= \{(x_1, y_1), (x_{2,} y_2), (x_{3,} y_i), \ldots.\} \tag{3.8}$$

Let say (i) is denoting for each unique element in the window, and (n) is the total number of all IP destination addresses for each window (W). Then, probability (P) of each unique IP destination address is calculated as shown in following equation:

$$p_i= \frac{y_i}{n} \tag{3.9}$$

Entropy (E) for each window can be calculated in equation (3.10). Then, the value of entropy may compare with certain threshold. if value of entropy is larger than the threshold, this means there are no attacks. However, if value of entropy is smaller than the threshold, this means there are attacks.

$$E= -\sum_{i=1}^{n} p_i \ln p_i \tag{3.10}$$

3.2.5 Cumulative Sum Detection (CUSUM)

CUSUM is an approach that is used to identify whether there is a small shift in the process mean from certain target or not. It is a sequential analysis method that is introduced by Page in [62]. CUSUM is the sum of accumulative samples that are deviated from target (M_0). If the results of summation are under certain threshold that is called decision interval (H), this means the operation of process is normal and within the target. However, if the

result of accumulative sum is equal or larger than decision interval (H), this means the process is out-of-control.

After flows are classified to either low-traffic flows or normal flow in the first step, percentages of low-traffic flows (X_i) are calculated by dividing number of low-traffic flows over number of all flows (normal and low-traffic flows) per timeslot. Target mean (M_0) is calculated by averaging all percentage values (dividing a summation of all percentage of low-traffic flows values by their number). The accumulative deviation, which is the summation of changes, can be calculated in two side. Upper side CUSUM (C_i^+) is calculated when there are change in the upper or positive side whereas lower side CUSUM (C_i^-) is calculated when there are change in lower or negative side. The upper and lower side CUSUM are computed as follow [62], [63]:

$$(C_i^+) = \text{Max} [\ 0, (C_{i-1}^+) + X_i - M_0 - K] \tag{3.11}$$

$$(C_i^-) = \text{Min} [\ 0, (C_{i-1}^-) + X_i - M_0 + K] \tag{3.12}$$

Where C_0^+ and C_0^- equal 0.

Allowance value or reference value which is (K) is chosen to be in middle of two values. These two values are target mean (M_0) and attack value of the mean (M_1) that would be detected fast. It can be computed as follow:

$$K = \frac{\delta}{2}\sigma = \frac{|M_1 - M_0|}{2} \tag{3.13}$$

Where (σ) is the standard deviation that calculated based on target mean (M_0) whereas (δ) is computed as follow:

$$\delta = \frac{|M_1 - M_0|}{\sigma} \tag{3.14}$$

If the value of upper side CUSUM (C_i^+) and lower side CUSUM (C_i^-) is larger than certain threshold (H), this means attack is detected. The value of (H) that suggested in [62] and [64] computed as follow:

$$H = d\ k \tag{3.15}$$

Where (d) is a function of false positive error (α), which is benign activities that are falsely identify as attack or shift in process, and false negative error (β), which is amount of shift or attacks that are falsely identified as benign. It is computed as follow:

$$d = \frac{2}{\delta^2} \ln\left(\frac{1-\beta}{\alpha}\right) \tag{3.16}$$

CUSUM method uses two counters which are (N^+) and (N^-) for (C_i^+) and (C_i^-) respectively to record when these two values start to increase above target mean (M_0). (N^+) and (N^-) increases by one when value of (C_i^+) and (C_i^-) shifts away from target mean. The reason for that is to know when attacks start to occur exactly by counting backward from the time that (C_i^+) and (C_i^-) values has exceeded (H) to time that these values start to shift from (M_0).

CHAPTER 4: RESULTS, EVALUATION AND DISCUSSION

4.1 Overview

This chapter presents the results of flow classification and detection algorithms that are explained in the previous section. Java is the programming language that is used to implement these algorithms. Defense Advanced Research Projects Agency (DARPA) datasets are used to evaluate our works.

4.2 Datasets

The datasets that are available in the Lincoln Laboratory website [17] is used to evaluate the detection algorithms. These datasets were captured by the group of Defense Advanced Research Projects Agency (DARPA) to evaluate computer network instruction detection systems. Some of these datasets were captured during 1998 while others were captured during 1999. The datasets that were captured during 1998 have one router that has one interface which is “00:00:0C:04:41:BC”. However, the datasets that were captured during 1999 have one router that has one interface which is “00:10:7B:38:46:32”. All main communications were passing through this interface. These two interfaces are considered as SDN switch interface in our case. These interfaces generated packet-in messages toward controller to overload it if they receive new flows from other interfaces that are connected to them. Therefore, we filtered out communication among other interfaces because they do not generate packet-in messages.

Four of these datasets were picked to do our evaluation, and they have the same name which is (outside tcpdump data). To recognize among them, we depended on dates

of capturing these datasets. Therefore, datasets that were used in our evaluation are (04/05/1999), (03/11/1999), (03/12/1999), and (07/03/1998).

4.3. Using Flows Classification in DARPA Dataset

We used jNetpcap library that is implemented in java to read packets from a dataset. Packets were grouped to unique flows based on packet header information. Three multimap tables of two columns and multiple rows were created to serve our needs. For the first multimap table, first column stored all unique flows whereas second column stored all packets that are belonged to each unique flow. As we mentioned earlier, "00:00:0C:04:41:BC" is the only MAC address number for the SDN switch for datasets that were captured during 1998. However, "00:10:7B:38:46:32" is the only MAC address number for the SDN switch for datasets that were captured during 1999. From the first multimap table, we need to get only flows that are injected to "00:00:0C:04:41:BC" if dataset is chosen from 1998 and "00:10:7B:38:46:32" if dataset is chosen from 1999.

To do that, we checked whether first packet for each flow has this MAC address as a destination address in their header or not. If this condition is yes, we created another multimap table, and we saved these flows in first column and number of each unique flows in the second column. However, we ignored the rest that do not have this condition. We did that because we need to know who start the connection. If the destination address in first packet is this MAC, we knew that switch interface is the receiver. Thus, if the receiver receives low-traffic flows, then switch will generate packet-in toward controller.

Finally, we classified all flows that exist in the second map table to either normal or low-traffic flows. We did that by comparing number of packets with certain threshold. The threshold is chosen to be (3) because normal TCP flow has at least three packets which

are three-ways handshaking of TCP protocol [6]. Therefore, if number of packets that belong to certain flow is larger than or equal to (3), the flow is normal, otherwise it is low-traffic flow. For example, the flow shown in figure 3.1 is normal flow because total number of packets are more than (3) packets. This process was applied to all flows that exist in the second multimap table. The results of classification were stored in the third multimap table.

4.4 Flow Classification Results

In this section, we picked four datasets to evaluate and present result of flow classification. These datasets are (04/05/1999), (03/11/1999), (03/12/1999), and (07/03/1998).

4.4.1 Results of Flows Classification for (04/05/1999) Dataset

This dataset contains (1299771) packets that have different protocols in their header. There are many types of DDoS attacks that were detected at different times in this dataset as mentioned in [6]. After gathering these packets to different flows, we got (51376) flows. Only (25762) have 00:10:7B:38:46:32 as destination in their first packet as shown in figure (4.1). After classifying these flows, we got (20732) low-traffic flows and the rest of them were normal as shown in table 3.

Dataset name	**Number of all packets in each dataset**	**Number of all Flows**	**Number of all flows that have 00:10:7B:38:46:32 as destination in the first packet of each flow**	**Number of low flows that have 00:10:7B:38:46:32 as destination in the first packet of each flow**	**Number of normal flows that have 00:10:7B:38:46:32 as destination in the first packet of each flow**
04/05/1999	1299771	51376	25762	20732	5030
03/11/1999	1339058	56725	14840	11482	3358
03/12/1999	1176620	49050	18055	15248	2807

Table 3: Statistics of Classification Flows Phase for 1999 Datasets

Vast number of low-traffic flows got generated at (9:43:11) as shown in figure (4.2). Portsweep attack was the reason for that. This attack is one of the scanner method that is used to probe the server ports to check which one is opened for the services. Attackers send one FIN packet to server. Server replies with RST,ACK packet if the port is closed, or it replies with ACK packet if port is opened [66].

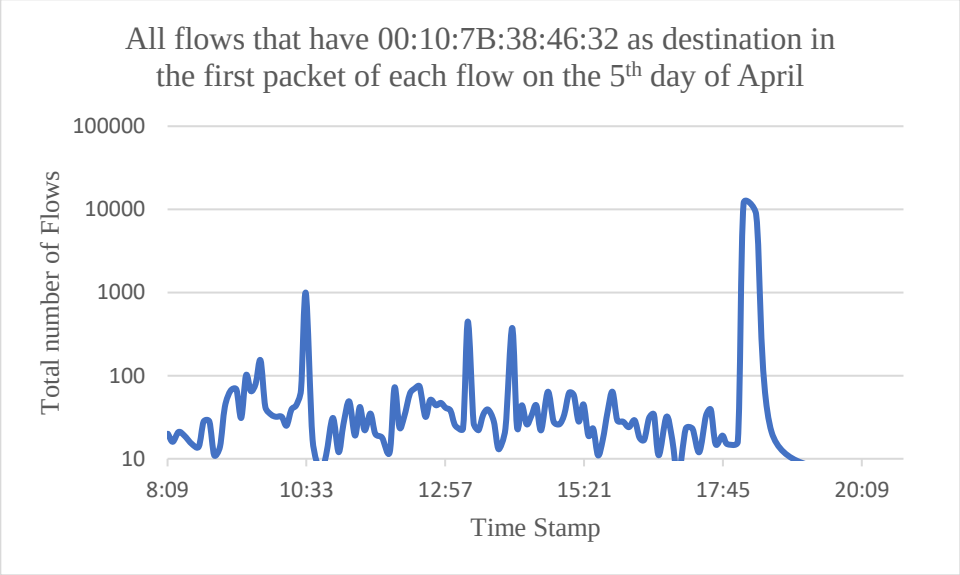


Figure 4.1 : All Flows that have 00:10:7B:38:46:32 as Destination Address in the First Packet of each Flow on the 5th day of April Dataset

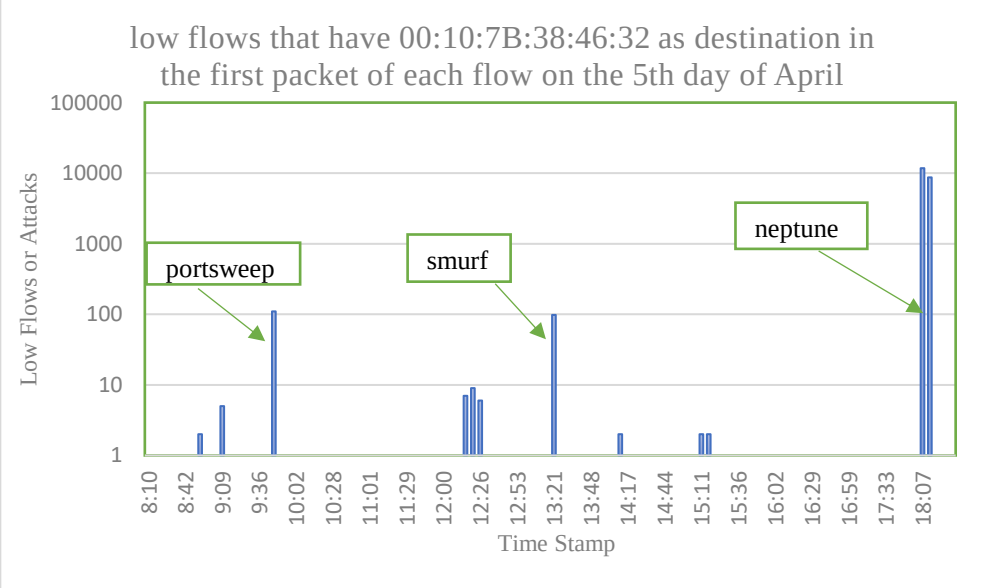


Figure 4.2: Low-Traffic Flows that have 00:10:7B:38:46:32 as Destination Address in the First Packet of each Flow on the 5th day of April Dataset

Even though intrusion detection methods do not consider portsweep as DDoS attacks, but attackers can use it to generate many low-traffic flows to trigger SDN switch to generate packet-in messages to overload the controller as stated in [6]. These types of scanners can pass through packet routers filtering and some type of firewalls [67] and lead to actual dangers in the future [68]. Thus, it is very important to consider them as an attack.

In addition, smurf attack that occurred at (13:18:12) also generated many low-traffic flows as shown in figure (4.2). Smurf uses spoofed IP that is usually like victim machine. Attackers may direct victim machine to send an ICMP protocol that contains echo asking for a reply to its broadcast address of its network. When victim does that, these IP addresses may reply with echo response that makes network unusable [69].

Finally, neptune attacks generated many low-traffic flows at (18:04:04) as shown in figure (4.2). In neptune attack, attacker sends SYN packets from its IP address or spoofed IP address to server to hide his identity. Then, server responses with a SYN/ACK packets to client, while client will not send back ACK packet. In this case, server may wait some time for each connection, and this consumes server resources and drops legitimate requests [70].

4.4.2 Results of Flows Classification for (03/11/1999) Dataset

This dataset contains (1339058) packets that different protocols in their headers. (56725) are the number of all flows after dividing these packets to unique flows as shown in table 3. The number of all flows that have (00:10:7B:38:46:32) as a destination Address in the First Packet of each Flow is (14840) as shown in figure (4.3).

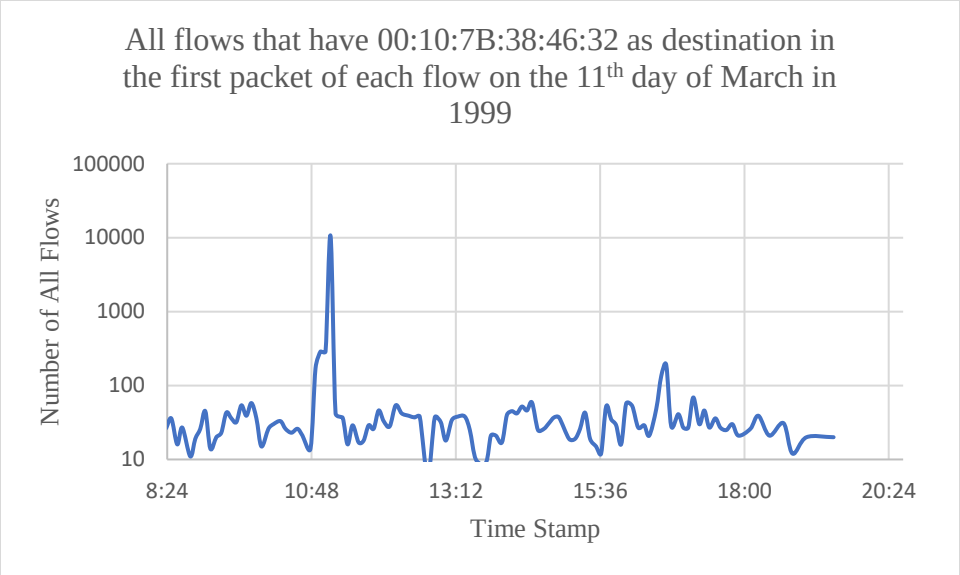


Figure 4.3: All Flows that have 00:10:7B:38:46:32 as Destination Address in the First Packet of each Flow on the 11th day of March in 1999 Dataset

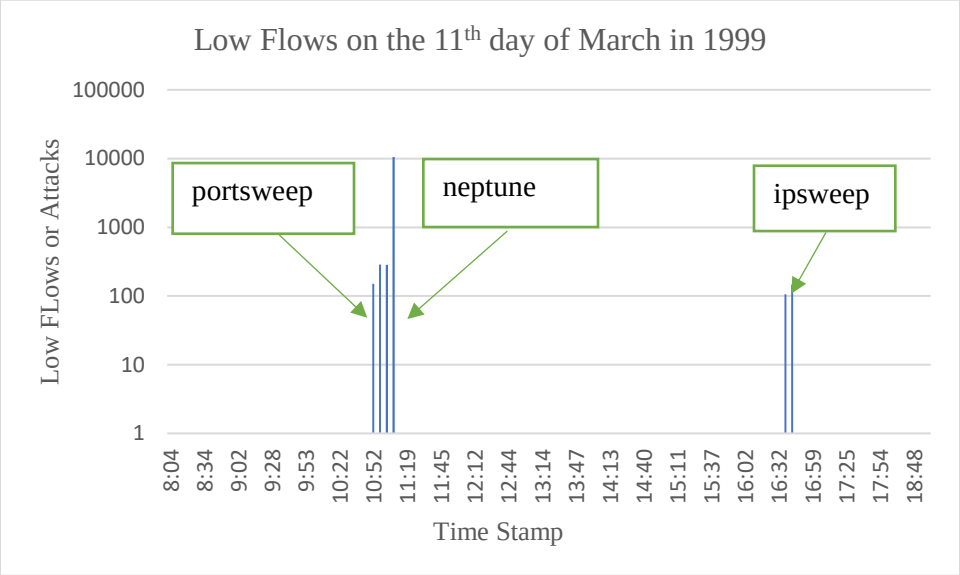


Figure 4.4: Low-Traffic Flows that have 00:10:7B:38:46:32 as Destination Address in the First Packet of each Flow on the 11th day of March in 1999 Dataset

This dataset produces (11482) flows that have (00:10:7B:38:46:32) as a destination Address in the First Packet of each Flow as in figure (4.4) . As stated in DARPA website, various types of DDoS attacks were detected at different times for this dataset. Portsweep generated many low-traffic flows attacks starting at (10:50:11). In addition,

another attack which is neptune or SYN flood attack leaded also to produce vast low-traffic flows at (11:04:16). Finally, at (16:36:10), ipsweep also generated many numbers of low attacks. ipsweep is like a probe network technique. In the legitimate cases, admin of network sends this probe to identify which machine is alive for the diagnosis purposes [68]. However, attackers can use this probe to serve its need. They can send to SDN switch large amount of ICMP echo packets that lead to create a table miss. In turn, compromised switch interface generates packet-in requests toward controller to overload it. This is kind of DDoS attacks that overloads the controller and refuse legitimate requests.

4.4.3 Results of Flows Classification for (03/12/1999) Dataset

This dataset has almost (1176620) packets. When we classified these packets to different flows, we got almost (49050) flows as shown in table 3. Because only flows that are injected to SDN switch would overload controller, we filtered out other flows. Thus, we got (18055) as total number of flows that are injected to SDN switch as shown in figure 4.5. These total number in figure 4.5 can be classified into (15248) as low-traffic flows and rest of them as normal. In figure 4.6, there are many new low-traffic flows that were generated at (11:20:15) which is a neptune attack. Finally, portsweep is another attack that produced low-traffic flows at 17:13:10.

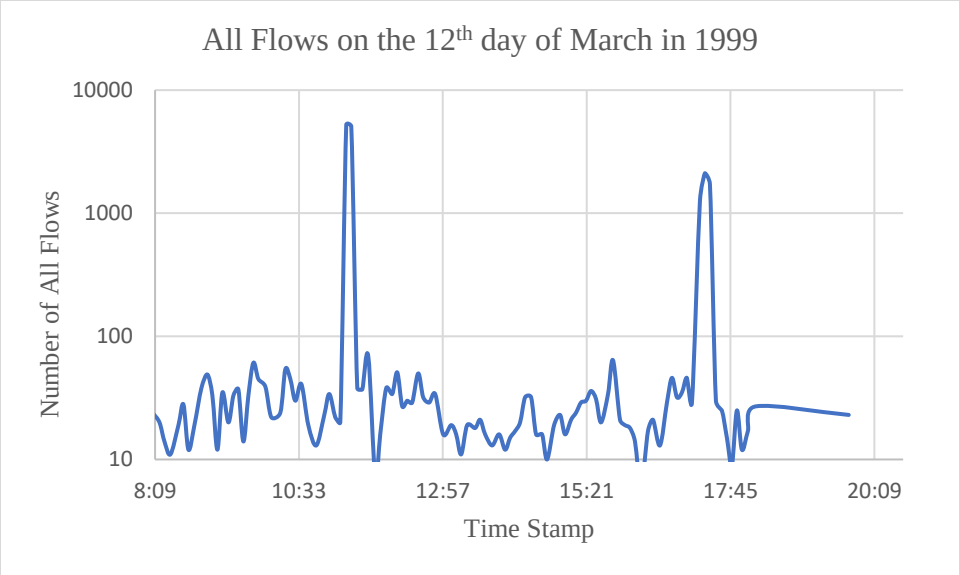


Figure 4.5: All Flows that have 00:10:7B:38:46:32 as Destination Address in the First Packet of each Flow on the 12th day of March in 1999 Dataset

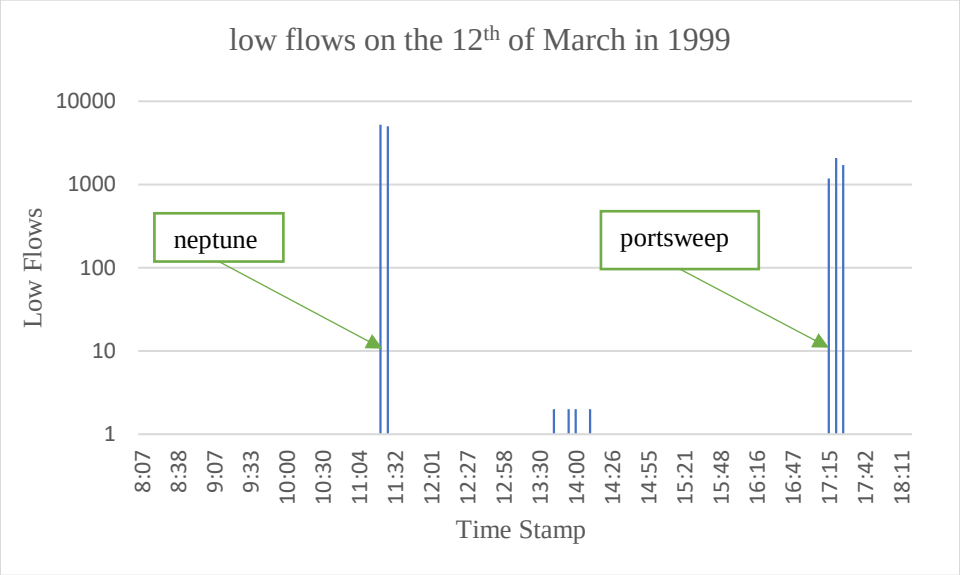


Figure 4.6: Low-Traffic Flows that have 00:10:7B:38:46:32 as Destination Address in the First Packet of each Flow on the 12th day of March in 1999 Dataset

4.4.4 Results of Flows Classification for (07/03/1998) Dataset

This dataset has almost one million packets as shown in table 4. These packets can be grouped to (256055) flows. The datasets that were captured during 1998 has one router

that has one interface which is “00:00:0C:04:41:BC”. Therefore, we need to get only these flows that are injected to this interface, which is considered as SDN switch in our case. We got (250551) flows that have this MAC address as destination in their first packet as shown in figure (4.7).

Dataset name	Number of all packets in each dataset	Number of all Flows	Number of all flows that have 00:00:0C:04:41:BC as destination in the first packet of each flow	Number of low flows that have 00:00:0C:04:41:BC as destination in the first packet of each flow	Number of normal flows that have 00:10:7B:38:46:32 as destination in the first packet of each flow
07/03/1998	1194920	256055	250551	243730	6821

Table 4: Statistics of Classification Flows phase for 1998 Dataset

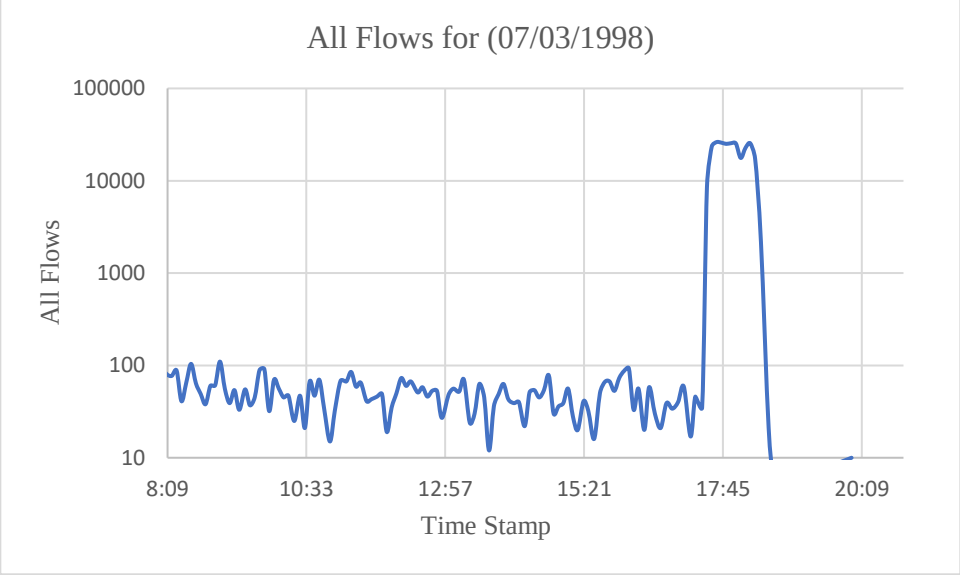


Figure 4.7: All Flows that have 00:00:0C:04:41:BC as Destination Address in the First Packet of each Flow for (07/03/1998) Dataset

There are many new low-traffic flows starting to occur at different time stamp for this dataset as mentioned in DARPA website and shown in figure (4.8). First, portsweep attack generated low flow starting at 11:46:39. Another attack which is neptune also produced many new flows at 17:27:07. Finally, at 18:00:15, smurf attack has started to occur as shown in figure below.

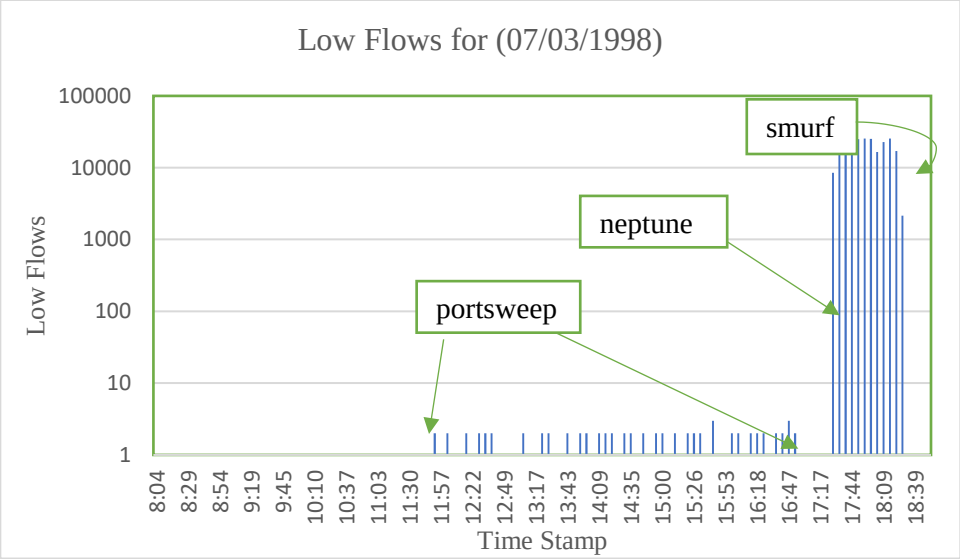


Figure 4.8: Low-Traffic Flows that have 00:00:0C:04:41:BC as Destination Address in the First Packet of each Flow for (07/03/1998) Dataset

4.5 Parameters of Detection Methods

First of all, SPRT needs four parameters in its algorithms as mentioned in section (3.2.1). These parameters are β, α, λ_0 and λ_1. It is better to choose a small value of β and α that are between 0.01 and 0.05 to limit the value of false negative error and false positive error as mentioned in [6] and [65]. As a result, we set β to be equal to (0.02) and α to (0.01). We also set λ_0= 0.33 and λ_1=0.6 because choosing these two values decreases the number of low-traffic flows observations that are needed to decide whether interface is compromised or not as mentioned in [6].

In addition, CD, PD, ED, and CUSUM depend on two important components which are windows size and threshold. First, window size for CD, PD and CUSUM methods are based on timeslot. We set their window size to be either almost every five minutes or ten minutes. However, window size for ED method is based on packets number. As suggested in [11] , number of packets in windows size should be set to be same as number of hosts in

the network. Thus, we set that to be 10 packets because number of hosts in the network of dataset is almost 10.

Second, we chose different threshold values which are 80, 150, and 250 in CD method. However, threshold value of PD was set to the following values: 0.2, 0.5, and 0.8. The reason for choosing different values is to observe reaction of each method with different threshold. However, the threshold of ED should set to be either 1.31 or 0.2 as suggested in [11] and [6]. Finally, M_1 or threshold of CUSUM algorithm was set to be either 0.4 or 0.8. We chose 0.4 because we need to detect out-of-control or low-traffic flows average value quickly. We also assumed M_1 to be 0.8 to compare results with previous threshold.

4.6 Detection Methods Results and Discussion

This section presents and compares results of the detection algorithms. SPRT, CD, PD, ED, and CUSUM are the detection algorithms that are used to show the results.

4.6.1 Results of Detection Algorithm for (04/05/1999) Dataset

On 5th of April 1999 dataset, three types of DDoS attacks named “portsweep”, “smurf”, and “neptune” occurred at “9:43:11”, “13:18:12”, and “18:04:04” respectively. All of these attacks produce vast and new of low-traffic flows as shown in figure (4.2). Table.5 summarizes results of all detection methods for this dataset.

Detection			**Detected Attacks (√)**		
Name	**Window size**	**Threshold**	**Portsweep**	**Smurf**	**Neptune**
SPRT	-	-	√	√	√
CD	5-minutes	80	√	√	√
CD	5-minutes	150			√
CD	5-minutes	250			√
CD	10-minutes	80	√	√	√
CD	10-minutes	150			√
CD	10-minutes	250			√

PD	5-minutes	0.2	√	√	√
PD	5-minutes	0.5	√		√
PD	5-minutes	0.8			√
PD	10-minutes	0.2	√	√	√
PD	10-minutes	0.5			√
PD	10-minutes	0.8			√
ED	10 packets	0.2		√	√
ED	10 packets	1.31		√	√
CUSUM	5-minutes	0.4	√		√
CUSUM	5-minutes	0.8			√
CUSUM	10-minutes	0.4	√		√
CUSUM	10-minutes	0.8			√

Table 5: Detected Attacks for All Detection Methods for (04/05/1999) Dataset

First of all, SPRT was able to detect all of these attacks. SPRT could decide that switch interface is compromised after observing only six continuous low-traffic flows. It also took only ten continuous normal flows observation to decide that interface is normal. These numbers are considered to be as minimum number of observations that are needed to take a decision.

In addition, CD generated same results when we chose different timeslot and produced different results when we chose different threshold. When we set threshold=80, CD detected all attacks that were detected by SPRT method. However, CD detected only “neptune” attack when threshold= 150 or 250. This means CD method produces false negative when threshold is high. Thus, it is a challenge to choose certain threshold and windows size to detect all attacks in CD method.

Furthermore, PD also depends on windows size and threshold in its implementation. First, PD was not able to identify “smurf” attack and produce false negative when we set windows size to 5-minute and choose threshold=0.5. When we changed that threshold to 0.8 with the same windows size, PD produced false negative at

"9:43:11" and "13:18:12" respectively. However, when we modified threshold to 0.2 with the same timeslot, PD method generated false positive at "12:15". Second, when we set timeslot to 10-minute with different threshold, we got different results. If threshold=0.2, PD detected all attacks. When threshold was 0.5 or 0.8, PD detected only neptune attack. Therefore, PD method has the same problem that is faced by CD method which is choosing an appropriate threshold and window size to get good output.

Finally, ED method generated false positive at "10:29" and false negative at "9:43" when windows size was 10 packets and threshold=1.31 or 0.2. CUSUM did not detect portsweep attacks when M_1 =0.8. It also identified "smurf" attack as a benign at "13:18" whether M_1=0.4 or 0.8. CUSUM faces difficulties of setting suitable windows size and threshold value to get accurate results. Finally, we got different results from CD, PD, ED, and CUSUM when we changed their main component values as shown results for 5th April dataset. Thus, it is challenging to choose these values to get accurate results.

4.6.2 Results of Detection Algorithm for (03/11/1999) Dataset

On 11th of March in 1999 dataset, three types of DDoS attacks named "portsweep", "neptune", and "ipsweep" occurred at "10:50:11", "11:04:16", and "16:36:10" respectively. All of these attacks generate new and vast number of low-traffic flows as shown in figure (4.4). Table.6 summarizes results of all detection methods for this dataset.

Detection			**Detected Attacks (√)**		
Name	**Window size**	**Threshold**	**portsweep**	**neptune**	**ipsweep**
SPRT	-	-	√	√	√
CD	5-minutes	80	√	√	√
CD	5-minutes	150	√	√	√
CD	5-minutes	250	√	√	
CD	10-minutes	80	√	√	√
CD	10-minutes	150	√	√	√
CD	10-minutes	250	√	√	

PD	5-minutes	0.2	√	√	√
PD	5-minutes	0.5	√	√	√
PD	5-minutes	0.8	√	√	√
PD	10-minutes	0.2	√	√	√
PD	10-minutes	0.5	√	√	√
PD	10-minutes	0.8	√	√	
ED	10 packets	0.2			√
ED	10 packets	1.31			√
CUSUM	5-minutes	0.4	√	√	√
CUSUM	5-minutes	0.8	√	√	√
CUSUM	10-minutes	0.4	√	√	√
CUSUM	10-minutes	0.8	√	√	√

Table 6: Detected Attacks for All Detection Methods for (03/11/1999) Dataset

First of all, SPRT identified all of these anomalies. The minimum number of low-traffic flows observations that were helped SPRT to decide that switch interface is compromise was only “6” whereas the maximum number of low-traffic flows observations was “20”. However, the minimum number of normal flows observations to decide that switch interface is normal was “10” whereas the maximum number was “19”.

Moreover, we used two timeslot sizes which are 5-minutes and 10-minutes with different thresholds to evaluate CD and PD method as mentioned earlier. CD generated false negative at “16:36:10” when timeslot and threshold were 5 or 10-minutes and 250 packets respectively. Furthermore, PD detected all attacks with window size of 5-minutes and all proposed threshold. However, it generated false negative at “16:38” when we set timeslot to10-minute and threshold=0.8.

Finally, ED was not able to detect “portsweep” and “neptune” and generated false negative at “10:50:11” and “11:04:16” with both threshold 1.31 and 0.2. CUSUM method identified all attacks on the 11th day of March dataset.

4.6.3 Results of Detection Algorithm for (03/12/1999) Dataset

On 12th day of March in 1999 dataset, two types of DDoS attacks named “neptune” and “portsweep” occurred at “11:20:15” and “17:13:10” respectively. All of these attacks generated new and vast numbers of low-traffic flows as shown in figure (4.6). Table.7 summarizes results of all detection methods for this dataset.

Detection			**Detected Attacks (√)**	
Name	**Window size**	**Threshold**	**Neptune**	**Portsweep**
SPRT	-	-	√	√
CD	5-minutes	80	√	√
CD	5-minutes	150	√	√
CD	5-minutes	250	√	√
CD	10-minutes	80	√	√
CD	10-minutes	150	√	√
CD	10-minutes	250	√	√
PD	5-minutes	0.2	√	√
PD	5-minutes	0.5	√	√
PD	5-minutes	0.8	√	√
PD	10-minutes	0.2	√	√
PD	10-minutes	0.5	√	√
PD	10-minutes	0.8	√	√
ED	10 packets	0.2	√	√
ED	10 packets	1.31	√	√
CUSUM	5-minutes	0.4	√	√
CUSUM	5-minutes	0.8	√	√
CUSUM	10-minutes	0.4	√	√
CUSUM	10-minutes	0.8	√	√

Table 7: Detected Attacks for All Detection Methods for (03/12/1999) Dataset

First of all, SPRT detected all of these attacks. SPRT decided that switch interface was compromised after observing “6” low-traffic flows which is the minimum number of low-traffic flows observation whereas the maximum number was 27. However, the minimum number of normal flows that were required to decide that switch interface as a

normal in this dataset was 10 whereas maximum number was 16. Finally, CD, PD, ED, and CUSUM detected all attacks for this dataset as shown in table 7.

4.6.4 Results of Detection Algorithm for (07/03/1998) Dataset

For this dataset, there are three attacks which are “portsweep”, “neptune”, and “smurf” that were started to occur at “11:46:39”, “17:27:07”, and “18:00:15” respectively as shown in figure (4.8). Table.8 summarizes results of all detection methods for this dataset. First of all, SPRT detected “neptune” and “smurf” attack because they were generated many new low-traffic flows. SPRT can decide that interface is compromised after observing 6 continuous low-traffic flows which are considered to be as a minimum number of observations whereas the maximum number of observation was 62. However, the minimum number of normal flows that are required to decide that switch interface is normal in this dataset is 10 whereas maximum number is 40.

Detection			**Detected Attacks (√)**		
Name	**Window size**	**Threshold**	**portsweep**	**neptune**	**smurf**
SPRT	-	-		√	√
CD	5-minutes	80		√	√
CD	5-minutes	150		√	√
CD	5-minutes	250		√	√
CD	10-minutes	80		√	√
CD	10-minutes	150		√	√
CD	10-minutes	250		√	√
PD	5-minutes	0.2		√	√
PD	5-minutes	0.5		√	√
PD	5-minutes	0.8		√	√
PD	10-minutes	0.2		√	√
PD	10-minutes	0.5		√	√
PD	10-minutes	0.8		√	√
ED	10 packets	0.2		√	√
ED	10 packets	1.31		√	√
CUSUM	5-minutes	0.4		√	√
CUSUM	5-minutes	0.8		√	√
CUSUM	10-minutes	0.4		√	√
CUSUM	10-minutes	0.8		√	√

Table 8: Detected Attacks for All Detection Methods for (07/03/1999) Dataset

On other hands, SPRT method was not able to detect “portsweep” attack although this attack produced low-traffic flows. This attack produces one low-traffic flow that was coming from a port which is 1234 toward a port from a group of 1-100 port every three minutes. This is like a DoS attack when an attacker attacks multiple machines from single machine. There are many flows were generated every three minutes, and most of them were normal flows. SPRT was taking its decision based on these normal flows. Thus, SPRT produces false negative and fails to detect attacks when low-traffic flows are distributed over long time periods. Finally, CD, PD, ED, and CUSUM failed to detect “portsweep” and generated false negative at “11:46:39”.

4.7 Evaluation of Detection Method by Confusion Matrix

We used confusion matrix that is mentioned in [71] to evaluate and compare all detection method. This matrix depends on four main components which are True Negative (TN), False Positive (FP), False Negative (FN), and True positive (TP). From these elements, many metrics can be computed. First of all, true positive rate (TPR) is the rate of number of malicious activities that are truly classified by classifier method as malicious. It also called sensitivity or recall, and it can be calculated from the following equation:

$$TPR=\frac{TP}{TP+FN} \tag{4.1}$$

True negative rate (TNR) is the rate of number of benign activities that are truly classified by classifier method as benign. It also called specificity, and it can be computed from the following equation:

$$TNR=\frac{TN}{TN+FP} \tag{4.2}$$

False positive rate (FPR) is rate of number of benign activities that are falsely classified as malicious activates. It also called fall-out, and it can be computed as in equation (4.3). False negative rate (FNR) is the rate of malicious activities that are falsely classified by classification stage as benign activities. It also called miss rate, and it can be computed as in equation (4.4):

$$FPR=\frac{FP}{FP+TN} \tag{4.3}$$

$$FNR=\frac{FN}{TP+FN} \tag{4.4}$$

In addition, positive predictive value (PPV) is the probability of intrusion detection that are truly predicted as attacks. It also called precision and can be calculated from equation (4.5). Negative prediction value (NPV) is probability of benign flows that are truly predicted by detection methods as benign. It can be computed as in (4.6).

$$PPV=\frac{TP}{TP+FP} \tag{4.5}$$

$$NPV=\frac{TN}{FN+TN} \tag{4.6}$$

False discovery rate (FDR) or probability of false alarm is the likelihood of benign activities that are incorrectly predicted as attacks, and it computed as in equation (4.7). False omission rate (FOR) is the rate of intrusion that are incorrectly predicted as benign and it can be computed as in equation (4.8). When results of TPR, TNR, PPV, and NPV for certain detection method are closed to 1 and results of FPR, FNR, FDR, and FOR is closed to 0, this means this detection method is good.

$$FDR = \frac{FP}{TP+FP} \tag{4.7}$$

$$FOR = \frac{FN}{FN+TN} \tag{4.8}$$

Finally, Accuracy of detection methods can be calculated as in equation (4.9). Prevalence is another metric, and it measures number of attacks affecting particular population of dataset. It can be computed as in (4.10). Because accuracy metric is not a good method to assess the performance of classifier or detection test, F_1 score can be used as another metric to measure accuracy of detection. It is a harmonic average of recall and precision, and it can be computed as in (4.11). It is between 0 and 1. When F_1 score is 0, performance of classifier is worst whereas when it is 1, performance of classifier is best.

$$Accuracy = \frac{TP+TN}{TP+TN+FN+FP} \tag{4.9}$$

$$Prevalence = \frac{TP+FN}{TP+TN+FN+FP} \tag{4.10}$$

$$F_1\ score = 2.\ \frac{PPV+TPR}{PPV+TPR} \tag{4.11}$$

4.7.1 Confusion Matrix Results for (04/05/1999) Dataset

Confusion matrix for this dataset was computed for all detection method to compare between them. First of all, we calculated TPR, FPR, TNR, FNR, PPV, FDR, FOR, and NPV for all detection methods. These values are between 0 and 1. The values of TPR, TNR, PPV, and NPV for SPRT method are very closed to 1 and results of FPR, FNR, FOR, and FDR for this detection method is very closed to 0 as shown in figure 4.9. This means this detection method is good. ED method has almost same results. However, value of FPR

is 0.35 and TNR is 0.64 for this method whether threshold was 1.31 or 0.2 as shown in figure 4.9.a and figure 4.9.b respectively.

CD, PD, and CUSUM produced very low TPR and very high FNR as shown in figure 4.9.a and figure 4.9.b respectively. CUSUM also produced 0.3 to 0.4 of FDR and 0.6 to 0.7 for PPV as shown in figure 4.9.c. Finally, we used abbreviation for all detection methods as shown in table 9 to make figure 4.8, figure 4.9, and figure 4.10 more clear.

Abbreviation	Name of Detection	Window size	Threshold
A	SPRT	-	-
B	CD	5-minutes	80
C	CD	5-minutes	150
D	CD	5-minutes	250
E	CD	10-minutes	80
F	CD	10-minutes	150
G	CD	10-minutes	250
H	PD	5-minutes	0.2
I	PD	5-minutes	0.5
J	PD	5-minutes	0.8
K	PD	10-minutes	0.2
L	PD	10-minutes	0.5
M	PD	10-minutes	0.8
N	ED	10 packets	0.2
O	ED	10 packets	1.31
P	CUSUM	5-minutes	0.4
Q	CUSUM	5-minutes	0.8
R	CUSUM	5-minutes	0.4
S	CUSUM	5-minutes	0.8

Table 9: Abbreviation for All Detection Methods

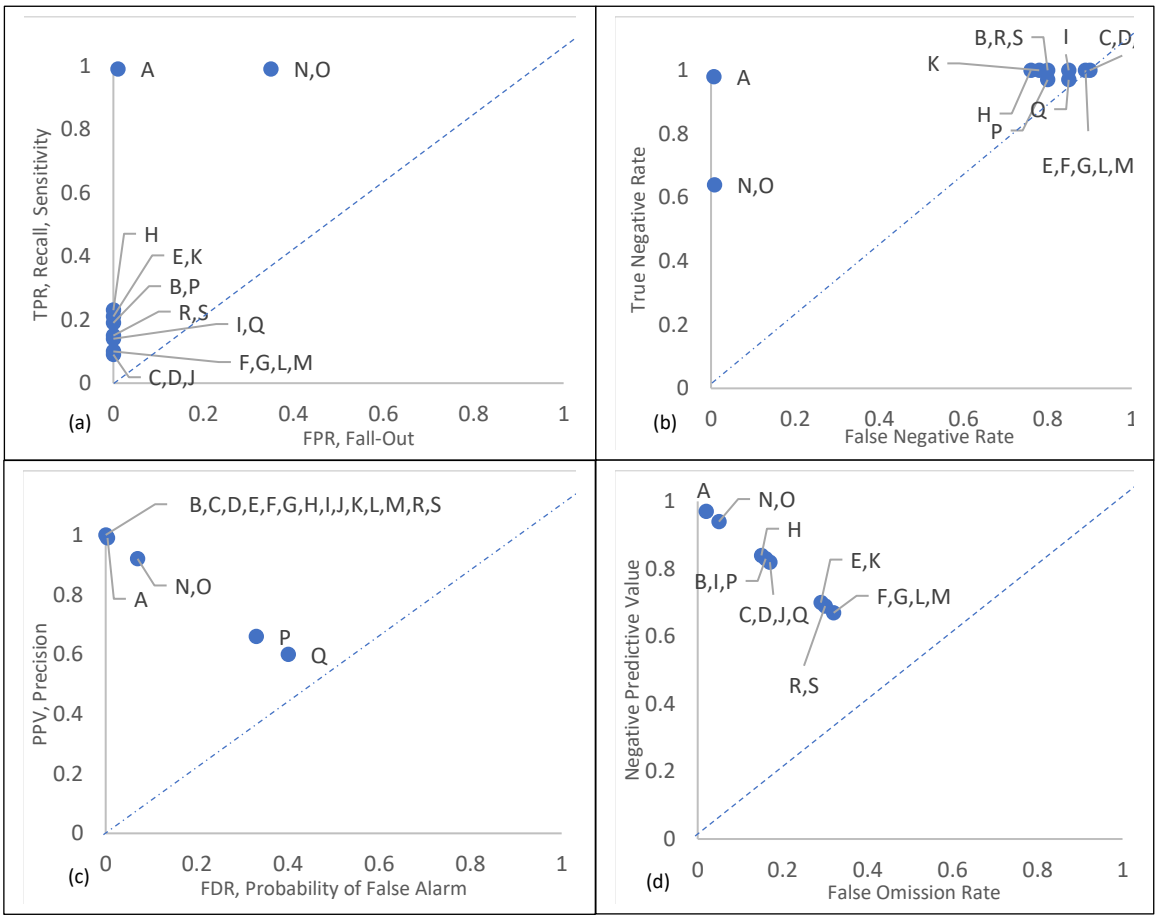


Figure 4.9 Graph Showing (a) TPR vs. FPR, (b) TNR vs. FNR, (c) PPV vs. FDP, (d) FOR vs. NPV for All Detection Methods for (04/05/1999) Dataset

Finally, values of prevalence, accuracy, and F1 score were presented in table 10. The value of prevalence for both SPRT and ED were the same which is 0.80 whereas the values of the rest were between 0.09 to 0.34. The value of accuracy and F1 score were 99% for SPRT which means it is a good detection method. ED had 92% of accuracy and 95% of F score. However, values of these two metrices for CD and PD were different. For example, value of accuracy of CD and PD was between 0.69 and 0.84 whereas value of F score was low. Finally, accuracy for CUSUM was between 70% to 80% whereas F score was between 0.23 to 0.29.

Detection			Prevalence	Accuracy	F1 score
Name	**Window size**	**Threshold**			
SPRT	-	-	0.80	0.99	0.99
CD	5-minutes	80	0.19	0.84	0.32
CD	5-minutes	150	0.19	0.82	0.17
CD	5-minutes	250	0.19	0.82	0.17
CD	10-minutes	80	0.34	0.72	0.34
CD	10-minutes	150	0.34	0.69	0.19
CD	10-minutes	250	0.34	0.69	0.19
PD	5-minutes	0.2	0.19	0.85	0.38
PD	5-minutes	0.5	0.19	0.83	0.25
PD	5-minutes	0.8	0.19	0.82	0.17
PD	10-minutes	0.2	0.34	0.72	0.34
PD	10-minutes	0.5	0.34	0.69	0.19
PD	10-minutes	0.8	0.34	0.69	0.19
ED	10 packets	0.2	0.80	0.92	0.95
ED	10 packets	1.31	0.80	0.92	0.95
CUSUM	5-minutes	0.4	0.19	0.82	0.29
CUSUM	5-minutes	0.8	0.19	0.81	0.23
CUSUM	10-minutes	0.4	0.34	0.7	0.27
CUSUM	10-minutes	0.8	0.34	0.7	0.27

Table 10: Value of Prevalence, Accuracy, and F1 for All Detection Methods for (04/05/1999) Dataset

4.7.2 Confusion Matrix Results for (03/11/1999) Dataset

The values of TPR, FPR, TNR, FNR, PPV, FDR, FOR, and NPV were calculated for all detection method for this dataset as shown in figure (4.10). First of all, SPRT produced high values of TPR, TNR, PPV, and NPV whereas it generated low values of FPR, FNR, FOR, and FDR. This is an indication that this detection method is good. However, ED has same results of SPRT, except that it produced high value of FOR and NPV as shown in figure 4.10.d.

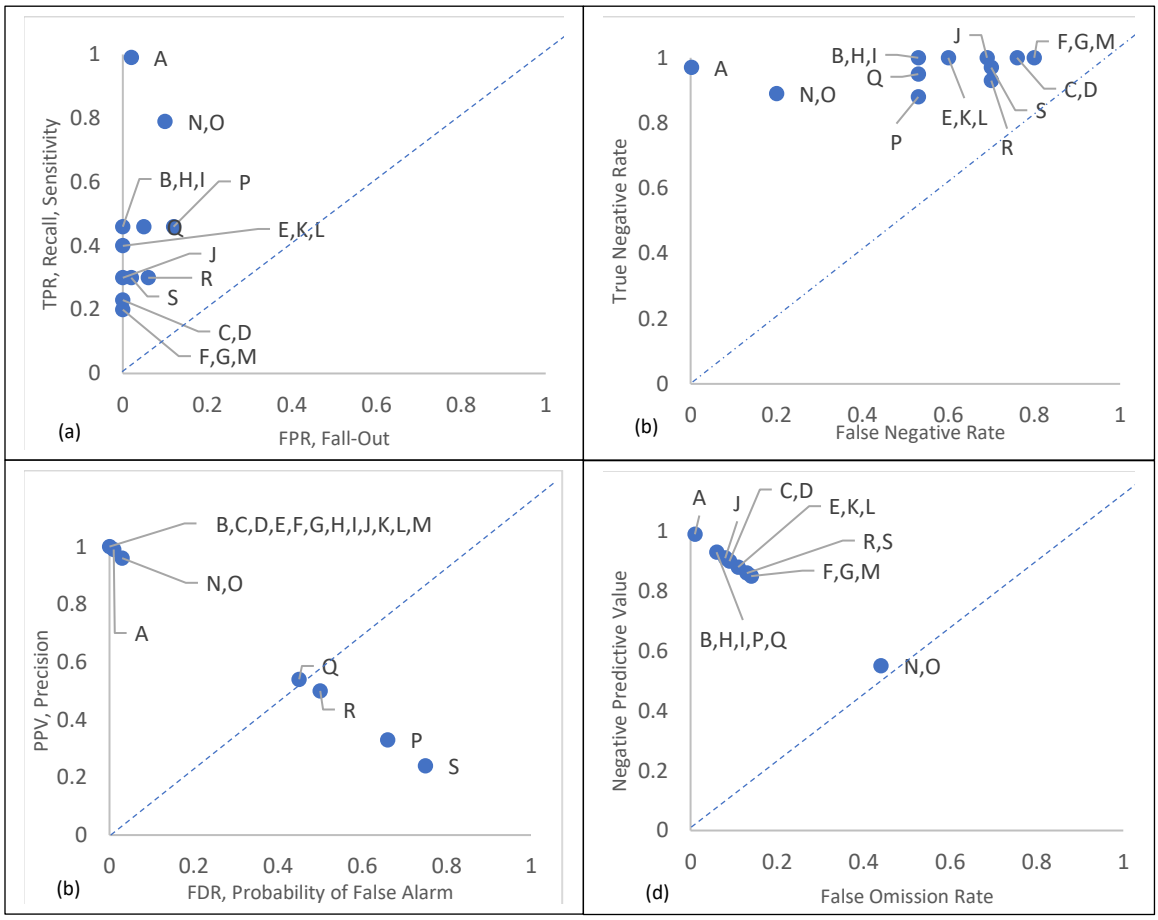


Figure 4.10 Graph Showing (a) TPR vs. FPR, (b) TNR vs. FNR, (c) PPV vs. FDP, (d) FOR vs. NPV for All Detection Methods for (03/11/1999) Dataset

Moreover, values of TPR for these PD, CD, CUSUM methods were almost between 0.2 to 0.4 as shown in figure 4.10.a whereas their values of FNR were between 0.53 to 0.8 as shown in figure 4.10.b. Finally, CUSUM generated low value of PPV and high value of FDR when threshold = 0.4 and window size = 5-minutes as shown in figure 4.10.c.

Finally, SPRT had 99% of accuracy and F score whereas ED has 81% and 86% for accuracy and of F score respectively as shown in table 11. On other hands, CD, PD, and CUSUM had accuracy between 82% and 93%, but the values of F score are between 33% and 63% which explains why these methods did not detect some DDoS attacks.

Detection			Prevalence	Accuracy	F1 score
Name	**Window size**	**Threshold**			
SPRT	-	-	0.77	0.99	0.99
CD	5-minutes	80	0.11	0.93	0.63
CD	5-minutes	150	0.11	0.91	0.37
CD	5-minutes	250	0.11	0.91	0.37
CD	10-minutes	80	0.17	0.89	0.57
CD	10-minutes	150	0.17	0.85	0.33
CD	10-minutes	250	0.17	0.85	0.33
PD	5-minutes	0.2	0.11	0.93	0.63
PD	5-minutes	0.5	0.11	0.93	0.63
PD	5-minutes	0.8	0.11	0.92	0.47
PD	10-minutes	0.2	0.17	0.89	0.57
PD	10-minutes	0.5	0.17	0.89	0.57
PD	10-minutes	0.8	0.17	0.85	0.33
ED	10 packets	0.2	0.77	0.81	0.86
ED	10 packets	1.31	0.77	0.81	0.86
CUSUM	5-minutes	0.4	0.11	0.83	0.38
CUSUM	5-minutes	0.8	0.11	0.83	0.38
CUSUM	10-minutes	0.4	0.17	0.82	0.37
CUSUM	10-minutes	0.8	0.17	0.85	0.42

Table 11: Value of Prevalence, Accuracy, and F1 for All Detection Methods for (03/11/1999) Dataset

4.7.3 Confusion Matrix Results for (03/12/1999) Dataset

SPRT generated high levels of specificity, sensitivity, precision, and NPV that are near to 1. It also produced low levels of fall out, miss rate, probability of false alarm, and FOR that are near to 0. This seems to be best case scenario that a good detection method should produce as shown on figure 4.11. ED had almost same results, except that values of specificity, NPV, and FOR is 0.88, 0.85, and 0.1 respectively as shown in figure 4.11.a and figure 4.11.d.

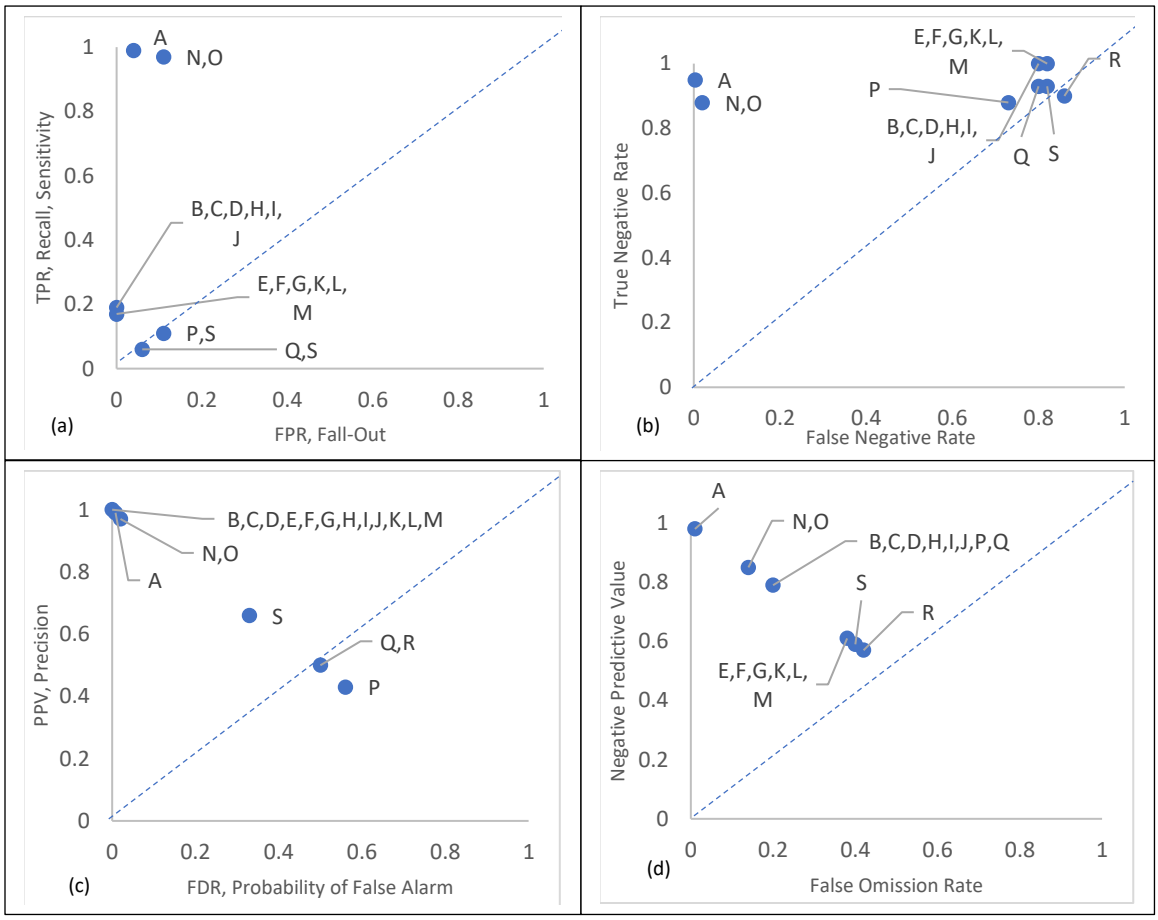


Figure 4.11 Graph Showing (a) TPR vs. FPR, (b) TNR vs. FNR, (c) PPV vs. FDP, (d) FOR vs. NPV for All Detection Methods for (03/12/1999) Dataset

In addition, CD, PD, and CUSUM produced very bad sensitivity which is almost 0 instead of 1 as shown in figure 4.11.a. They also had value of miss rate close to 1 instead of 0 as shown 4.11.b. CUSUM produced values between 02 to 0.4 of FOR. Finally, it generated low level of PPV and high level of FDP as in 4.11.c.

Finally, table 12 shows results of prevalence, accuracy, and F1 score. First of all, SPRT and ED produced good value of these metrices. In addition, PD, CD, and CUSUM

had values of prevalence between 0.24 and 0.43. They also had bad results of F1 score which are between 0.29 and 0.32, and their accuracies between 56% to 80%.

Detection			Prevalence	Accuracy	F1 score
Name	**Window size**	**Threshold**			
SPRT	-	-	0.84	0.99	0.99
CD	5-minutes	80	0.24	0.80	0.32
CD	5-minutes	150	0.24	0.80	0.32
CD	5-minutes	250	0.24	0.80	0.32
CD	10-minutes	80	0.43	0.64	0.29
CD	10-minutes	150	0.43	0.64	0.29
CD	10-minutes	250	0.43	0.64	0.29
PD	5-minutes	0.2	0.24	0.80	0.32
PD	5-minutes	0.5	0.24	0.80	0.32
PD	5-minutes	0.8	0.24	0.80	0.32
PD	10-minutes	0.2	0.43	0.64	0.29
PD	10-minutes	0.5	0.43	0.64	0.29
PD	10-minutes	0.8	0.43	0.64	0.29
ED	10 packets	0.2	0.84	0.95	0.97
ED	10 packets	1.31	0.84	0.95	0.97
CUSUM	5-minutes	0.4	0.24	0.73	0.33
CUSUM	5-minutes	0.8	0.24	0.75	0.27
CUSUM	10-minutes	0.4	0.43	0.56	0.20
CUSUM	10-minutes	0.8	0.43	0.60	0.27

Table 12: Value of Prevalence, Accuracy, and F1 for All Detection Methods for (03/12/1999) Dataset

4.7.4 Confusion Matrix Results for (07/03/1998) Dataset

This dataset likes other previous datasets in which SPRT and ED had good results of TPR, FPR, TNR, FNR, PPV, FDP, NPV, and FOR as shown in figure 4.12. The only exception is that ED had 0.72 of NPV and 0.27 of FOR, but it is still better than other detections methods.

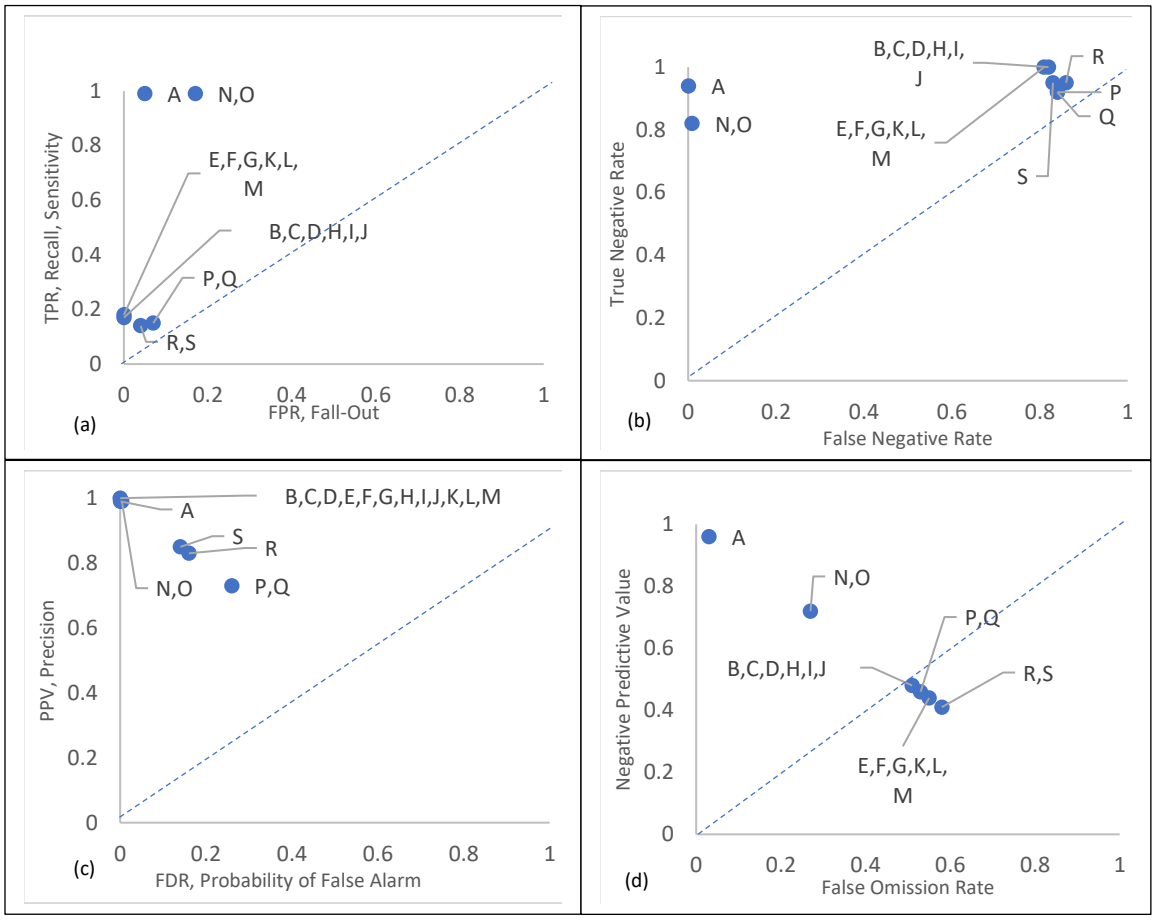


Figure 4.12 Graph Showing (a) TPR vs. FPR, (b) TNR vs. FNR, (c) PPV vs. FDP, (d) FOR vs. NPV for All Detection Methods for (07/03/1998) Dataset

PD, CD, and CUSUM had low values of TPR and high value if FNR as shown in figure 4.12.a and figure 4.12.b respectively. Finally, SPRT and ED had 99% of accuracy and F1 score. PD, CD, and CUSUM had accuracies between 45% to 53% and F1 score between 23% to 31%.

Detection			Prevalence	Accuracy	F1 score
Name	**Window size**	**Threshold**			
SPRT	-	-	0.97	0.99	0.99
CD	5-minutes	80	0.56	0.53	0.29
CD	5-minutes	150	0.56	0.53	0.29
CD	5-minutes	250	0.56	0.53	0.29
CD	10-minutes	80	0.60	0.50	0.31
CD	10-minutes	150	0.60	0.50	0.31
CD	10-minutes	250	0.60	0.50	0.31
PD	5-minutes	0.2	0.56	0.53	0.29
PD	5-minutes	0.5	0.56	0.53	0.29
PD	5-minutes	0.8	0.56	0.53	0.29
PD	10-minutes	0.2	0.60	0.50	0.31
PD	10-minutes	0.5	0.60	0.50	0.31
PD	10-minutes	0.8	0.60	0.50	0.31
ED	10 packets	0.2	0.97	0.98	0.99
ED	10 packets	1.31	0.97	0.98	0.99
CUSUM	5-minutes	0.4	0.56	0.49	0.26
CUSUM	5-minutes	0.8	0.56	0.49	0.26
CUSUM	10-minutes	0.4	0.6	0.45	0.23
CUSUM	10-minutes	0.8	0.6	0.47	0.27

Table 13: Value of Prevalence, Accuracy, and F1 for All Detection Methods for (07/03/1998) Dataset

CHAPTER 5: CONCLUSION

5.1 Conclusion

The SDN makes networks design more flexible, cheaper, and programmable because it separates the control plane from the data plane. The SDN gives administrators of networks more flexibility to handle the whole network by using one device which is the controller. Unfortunately, the controller of the SDN faces the dangers of DDoS attacks. Attackers trigger their switches to generate large number of packet-in messages toward controller when they send new and vast numbers of low-traffic flows to switches. This leads to DDoS attacks against the SDN controller. DDoS attacks can reduce system availability and bring the network down.

We conducted a comparative study of a set of methods for detecting the DDoS attacks on the controller of SDN and identifying compromised switch interfaces. Because attackers generated new and low-traffic flows, flows were classified to either low-traffic flows or normal flows. Results of classification were as an input for detection methods. These methods are SPRT, CD, PD, ED, and CUSUM. These methods are based on statistical approaches. DARPA dataset were used to evaluate these methods. The datasets that were used in our evaluation are (04/05/1999), (03/11/1999), (03/12/1999), and (07/03/1998).

In addition, CD, PD, ED, and CUSUM have two main components: windows size and threshold. These algorithms need to divide dataset to small window sizes that are based

on either timeslot or packets number. The window size of CD, PD, and CUSUM was based on timeslot whereas window size for ED was based on number of packets. Table 14 shows the overall mean of detected attacks for all detection methods. First of all, the overall mean of detected attacks for SPRT was 0.91. Furthermore, the overall mean of detected attacks for CD and PD fall between 0.66 and 0.91 whereas overall average of detected attacks for CUSUM fall between 0.74 and 0.83. Finally, ED has 0.66 of overall average of detected attacks.

Detection			Overall Mean
Name	**Window size**	**Threshold**	
SPRT	-	-	0.91
CD	5-minutes	80	0.91
CD	5-minutes	150	0.74
CD	5-minutes	250	0.66
CD	10-minutes	80	0.91
CD	10-minutes	150	0.74
CD	10-minutes	250	0.66
PD	5-minutes	0.2	0.91
PD	5-minutes	0.5	0.83
PD	5-minutes	0.8	0.74
PD	10-minutes	0.2	0.91
PD	10-minutes	0.5	0.74
PD	10-minutes	0.8	0.66
ED	10 packets	0.2	0.66
ED	10 packets	1.31	0.66
CUSUM	5-minutes	0.4	0.83
CUSUM	5-minutes	0.8	0.74
CUSUM	10-minutes	0.4	0.83
CUSUM	10-minutes	0.8	0.74

Table 14: Overall Mean of Detected Attacks for all Datasets

We found that SPRT had 99% of accuracy and F score which means it is good detection method. Values of TPR, TNR, PPV, and NPV for all datasets were almost closed to 1 whereas values of FPR, FNR, FOR, and FDR were almost closed 0. SPRT detected

all attacks without producing false positive or false negative when sequence of continuous low-traffic flows was generated for certain amount of time. However, SPRT produced false negative and failed to detect attacks when low-traffic flows were distributed over long time periods as shown on the 3th day of July in 1998 dataset.

ED produced different results for each dataset. It had accuracy values that fall between 81% and 98% whereas F score values fall between 86% and 99%. This method generated values of FOR that fall between 0 and 0.44 whereas values of FPR fall between 0 and 0.35. Values of FNR and FDR close to 0. However, values of TPR and PPV close to 1. Finally, values of TNR fall between 1 and 0.64 whereas NPV values fall between 1 and 0.55. ED was not able to detect some DDoS attacks such as portsweep on the 5th day of April in 1999 dataset, portsweep and neptune on the 11th day of March in 1999 dataset, and portsweep for 3th day of July in 1998 dataset.

In addition, CD and PD methods produced low number of TPR and high number of FNR. This decreases both of accuracy and F score values. The values of accuracy for CD and PD fall between 50 and 93 whereas values of F score fall 29 and 63. Moreover, CUSUM method has values of accuracy fall between 45 and 83 whereas values of F score fall between 20 and 42. Finally, PD, CD, and CUSUM algorithms produced different results when values of their components were changed. They are also failed to detect some attacks. Therefore, it is challenging to set appropriate values of window size or threshold to get accurate detection results.

5.2 Future Work

For future work, I am planning to study other new methods based on statistical approaches to discover their effectiveness to detect the DDoS attacks and protect the

controller of the SDN. I am also planning to explore the machine learning algorithms to determine their ability in identifying the DDoS attacks against the controller of the SDN.

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